Artificial Intelligence and Big Data in Finance: Enhancing Investment Strategies and Client Insights in Wealth Management

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Abstract: ***The emergence of AI technologies in the finance industry has become increasingly prominent due to the growing prevalence of data. Recent advancement of AI technology and big data can notably improve efficiency in fund allocation and financial risk management, which eventually give rise to new opportunities for wealth management firms. The emergence of automatic trading has opened a new world for individuals with little financial investment ability. However, the wealth-management services that financial consulting companies offer still have high thresholds and fees, and are often not reachable by ordinary people. Startups of wealth management attempting to bridge the gap have emerged in China to provide services based on the normal users' credit data from e-commerce and network service providers. Nevertheless, the investment experts involved in the startups usually rely on prior knowledge and financial heuristics to go through their task instead of sophisticated intelligent methods. Advances in AI technologies such as automatic style recognition and natural language processing can allow machines to replace laborers to provide interactive services to customers. These technologies have the potentials to facilitate the subsequent work of finance and big data to bridge the gap by combining financial intelligence with AI in the construction of a financial brain, which refers to an inclusive intelligent toolbox supplying kinds of traditional professional financial services/quasi-financial services to meet the various financial needs of ordinary people. The security and reliability of making money that are as important as investment-style match, must remain at the forefront of consideration. Comprehensive analysis to weigh certain chosen intelligent and classic technologies should be exploited to construct models and products.***

Keywords: AI-driven Investment Strategies, Big Data Analytics, Wealth Management Technology, Machine Learning in Finance, Client Insights, Predictive Analytics, Financial Data Modeling, Algorithmic Trading, Risk Management with AI, Personalized Financial Advice, Data-Driven Investment Decisions, Financial Forecasting, AI in Portfolio Management, Blockchain in Wealth Management, Customer Segmentation with Big Data.

1. Introduction

Artificial intelligence (AI) and big data have been transforming the finance sector thanks to the great advances in the rapidly-evolving AI technologies and the widely-used big data availability. The massive and high-dimensional big finance data from diverse data sources and multi-channels pose huge challenges on how to effectively identify, explore and understand the useful and event-underlying knowledge. The increasing complexity and high dynamics of finance events, behaviors and systems raise urgent challenges on how to effectively model, characterize, optimize and manage their behavior and working mechanisms. New AI technologies, with widely-used big finance data and growing strength of computing capability and power for distributed storage and processing, give birth to new opportunities and tools for the above challenges. Compared to traditional data-driven and decision-oriented applications, modern AI applications in finance center on finance data analysis model-oriented understanding and insight discovery, with modeling, representation and exploration beyond data analysis and insight management.

On the one hand, AI technologies can be seen as the tools and engines for learning from experience and knowledge, deriving pattern and insight, and providing intelligence and wisdom for smart decision making and control. Machine learning has been widely used in stock, credit and anti-money laundering, among others. On the other hand, AI can also be viewed as information-driven systematic, mathematical and statics modeling and computation methods and tools for understanding, on-site/in-situ behavior representation and insight discovery from various kinds of knowledge and artificial complex system modeling, representation and exploration. As big data keeps growing, the sensing capability and power of the modern AI technologies keep exploding, finding the traditional working mechanisms with classical analytics and learning methods are not enough as they are often unstructured. This provides a great incentive that big data complements the current state-of-the-art AI technologies for large, complicated and dynamic events and systems.

Value investing is a timeless and effective investment strategy based on fundamentals. It enjoyed great popularity in the early 20th century, which was eventually implemented as an AI-driven information aggregation and arbitrage process. Tech stocks were overvalued in the late 1990s; basically, a transformation of the whole economic structure in the United States caused a massive decline of tech stock prices, since when value investing has been widely regarded as passive or low-risk and low-return investment, lagged behind growth investment such as momentum trading. The former is solely based on fundamentals of a company but often blind to multi-faceted news signals; the latter normally capitalizes on whimsical afterthoughts of, predictions to, as well as collective behaviors and opinions on stocks regarding their likely price movements. In reality, AI-driven news dissemination, valuation, trading, and wealth accumulation are talent-sourced and wisdom aggregated top-down automated processes.

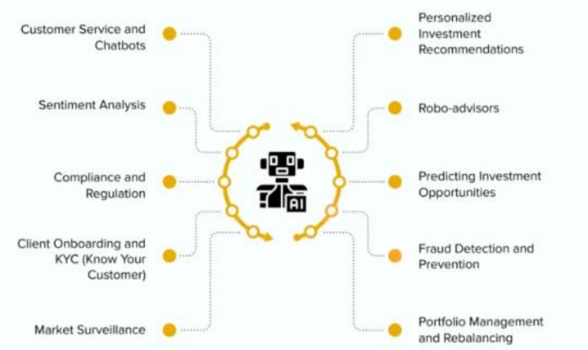

Figure 1: Client Insights in Wealth Management

1.1 Background and Significance

Finance is a vital infrastructure for the sustainable development of economy and society, enabling the exchange of wealth, experience, and information, the valuation of assets and capital flow, and the investment of return and risk management. Finance is a system of input, transfer, and output, based on the mutual recognition of the value of wealth, people's confidence, efficiency of information dissemination, and sustainability of development, in which an initiator supplies wealth and seekers acquire wealth through a capital-flowing process. Many factors affect the participants' trust behaviors of commitment and assurance and their credit assessment, including general, industry-specific, and event-specific news, understanding and assessment of the events, item-item relationship between the news items, and time and geographical position in which the messages and understanding appear. With the increasing online news coverage, the rapid accumulation of news has made it difficult for investors and financial analysts to track all the relevant news items that might impact the stocks they were interested in. It has been an important task to automatically filter out relevant news items since irrelevant items would increase the cost, time, and noise. News categorization and filtering, which aims at identifying news snippets that contain important news relevant to a specific category of stocks, is an efficient way to tackle this problem.

Equ: 1 Portfolio Optimization (Mean-Variance Optimization with AI-adjusted Returns)

$$\max_{\mathbf{w}} \left(\mathbf{w}^\top \hat{\boldsymbol{\mu}}_{AI} - \frac{\lambda}{2} \mathbf{w}^\top \Sigma \mathbf{w} \right)$$

- $\mathbf{w}$: Portfolio weights
- $\hat{\boldsymbol{\mu}}_{AI}$: AI-predicted expected returns vector
- Σ: Covariance matrix of asset returns
- λ: Risk aversion parameter

2. Understanding Artificial Intelligence

Artificial Intelligence (AI) is a field that engages computer systems in problem-solving tasks that would require intelligence when performed by humans or animals. It can be divided into a list of seven layers: infrastructure, data, algorithms, applications, interactions, ethical considerations, and universal concerns. AI is a powerful tool for data-driven activity and the fourth industrial revolution. In various aspects, AI expansion can lead to the obsolescence of entire industries, leaving behind many to find work as convenience stores and food couriers.

The global finance community has long been using mathematical-based algorithms and computational data analysis for market prediction, company value assessment, risk management, and margin control to maintain fairness and transparency at all stages of economic development. During the second wave of AI popularization in 2011, new financial AI applications were developed and put into action. Comprehensively understanding the AI-related challenges, techniques, and opportunities in the comprehensive finance picture is crucial to developing fin-tech and ESG. Therefore, it is essential to identify the different components and interactions among these AI-related topics regarding diverse challenges, different techniques, research opportunities, and application potentials, as well as their associated AI models and data sets.

2.1 Definition and Scope

Artificial intelligence (AI) and big data (BD) are two of the most cross-disciplinary research and application areas in both computer science and various domains, such as finance, economics, business, government, society, health, transportation, environmental protection, education, science, and technologies. Smart finance, economy, and society refer to the applications of AI and BD technologies, methods, tools, and theories in finance, economics, business, and others. There has been intensively increasing research and development involving the above topics and concerns globally. The general agenda is to synthesize and develop theory-informed methodologies, technologies, and tools to tackle the challenging problems, opportunities, theories, and technologies of implementing AI and BD in eco-fin systems for synthetic financial technology, smart finance, economics, and society.

The growing amount of complex data has attracted a lot of attention in recent years for financial knowledge discovery and finance behavior understanding. Traditional efforts in finance and economics include both analytical modeling approaches of mathematical theory and learning approaches of statistical theory. Such mathematical or statistical modeling, mostly based on the known data and domain knowledge, is so far the main efforts and achievements in finance and economics. These approaches greatly improved the intelligent faults detection techniques, safety of transportation systems, fuel-efficient operations, efficiency of port operations, etc. Recent years have seen a great upsurge of computational intelligence in the domains of finance and economics with the most active efforts on heuristic search algorithms, decision architectures and simulation, soft computing, dynamic programming, etc. Most of these approaches use limited finance theory or knowledge. There has been to date no comprehensive theoretical framework, methodology, technology, and tool to incorporate both AI and finance appropriately and intelligently for eco-fin knowledge discovery, behavior understanding, mechanism modeling, simulation, analysis, optimization, and prediction.

2.2 Types of AI Technologies

AI is the simulation of human intelligence processes by machines, especially computer systems. AI techniques can either be 'rules-based' or 'learned,' and further classified into discrete AI and deep learning (DL) or traditional machine learning (TML) approaches. AI rules (or knowledge) are based on information generally considered to be true and whose consequence would likely also be true if the information were true. Issue coverage, information precision and accuracy, and valuations on truth degree all affect the implication certainty. Data points of interest are analyzed based on the rules, or rules are instead inferred from the data directly used without prior knowledge of the working processes to derive hidden properties of the EcoFin data generating process. AI technologies are generally classified as either knowledge crafted AI or learned AI. TML techniques learn a function to implicitly or explicitly derive mapping characteristics from data features through various types of models, traditional normalized or customized holonomic systems such as regressors, decision trees, support vector machines, random forests, etc. Deep learning employs deep neural networks usually with multiple hidden layers. Data stimuli are vectorized and transformed through inter-layer or inter-node information exchange. Nodes act as binary or linear thresholds and a stochastic random choice process.
AI technologies are actively and extensively used in finance because of the large data often involved. They are applied in continual processes of data acquisition and preprocessing, processing and analysis, knowledge elicitation, and economic or financial behavior strategy discovery, analysis, and interpretation. It is therefore very valuable for the AI and FinTech communities to exchange and share usage experiences and lessons learned with each other. In particular, AI technology taxonomy is useful for the AI community for a deep understanding of FinTech problems and extreme events. For example, AI technology features are highly insightful for analyzing crypto currency data and the advantages and limits characteristics of different sorts of AI methodologies.

FinTech usage of modern AI technologies is meaningful and extremely insightful for the AI community for a deeper understanding of economic and financial domains, and the challenging and unique characteristics and complexities of the corresponding problems, including supply and demand, macro and micro fractal layers, heterogeneous agents and entities, spatiotemporal high dynamics, and behavior feedback loops. Challenges include discoveries of the multi-level causality, inferential granularity, and topology, weapon secrets and information, etc. Analysis of the impacts of AI-driven sensationalities and behaviors on the system-level workings through the elicited mechanisms is significantly insightful for understanding economic and financial systems.

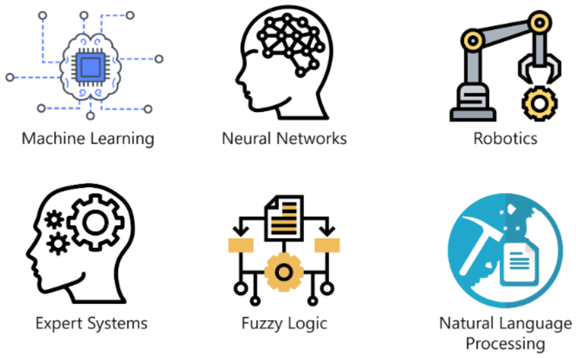

Figure 2: Types of Artificial Intelligence (AI)

2.3 Applications in Finance

By 2021, through AI embedded big data, business innovation, organic growth, and rich open data sources, data-driven financial modeling is envisioned to arise deep distributed applications, modeling, and intelligence across Internet finance for R&D and capital raising, mobile payments and trading for funds transfer and transactions, digitized asset management for investment and trading, and crowd-funding for investment and capital raising. With more data and challenging tasks, a deep part of mathematics and computer science and syndication of diverse knowledge can be expected in deep distributed modelling. By 2021, powerful and broad deep data-driven financial modeling is expected to reduce the complexity of big data and therefore help to better understand, model, and anticipate challenging capabilities of the finance industry in answering “What will happen?” or “What is going on?”. The economics and finance communities are witnessing increasing challenges and opportunities for applications of AI. Notably,. Statistical and mathematical modeling techniques have been applied in economics and finance since the 1970s, both for basic research and industry practices. Data analytics, machine learning, and AI to some extent started to be introduced to finance five or six years ago, initially for building wealth management for consumer banks to influx clients and in the secondary market. However, most industrial applications currently focus on some very simple AI techniques to gain some financial insights. On the academic side, similar discussions exist. It is no surprise that FuDing, a new experimental complementary tool for economists, is being incorporated to explain EcoFin. On the other hand, in terms of AI-driven anticipated innovations, not much has been observed in economics, finance, and business domains. More surprisingly, even existing AI driven works seemed to be superficially aware of AI with a very intuitive or plain view and therefore very shallow applications of deep models. Either on the academic or industrial applications side, a very deep understanding of advanced mathematics, statistics, and computer sciences would be needed for diverse desired capabilities of modelling with big data in the complex Eco-finance system, as well as basic models.

3. Big Data in Finance

The structured nature of financial data makes it far more regional and bounded than unstructured data. Market prices of shares and interest rates of bonds are subsequently fed into a variety of models to estimate risk and predict the way data will evolve. All of these models rely on the particular characteristics of the time series representation of data which governs the very diffusion of prices and rates. However, the efficient market hypothesis implies that theoretically, the arrival of news and the subsequent change of market prices is random. Moreover, trading volumes, which according to traditional theory are inferred by price movements, can be treated as leading variables for market prices and market risk measures. Time series representations of data may incorporate noise or "fractal" noise, which would yield an incorrect representation of market dynamics.

The theory of complex systems proposes an alternative representation in which time series are modeled as a series of grand events, soft and quick news, and attended with long-lasting excitement. As a result, financial and macroeconomic data may be treated differently and inspired from physics. Spheres of equilibrium are then extracted which are separating one basin of attraction from another. The financial regulator and/or the monetary authority are depicted in this framework. They are entrusted with the task of managing the expensive machinery of such a complex system. The latter has very specific criteria on which interventions can be robust. Ultimately, this system appends a new layer of causality in addition to the standard economic reasoning.

The multitude of complex behaviors in the financial markets and in the continuous financial news originating from various financial information sources present a significant challenge for practical risk management. These challenges can be addressed through continuous acquisition of large financial news datasets, applying natural language processing methods, exploring the temporal and network structures of the news, and integrating this big data with traditional numeric data using a hybrid big data risk management framework.

Equ: 2 Client Segmentation via Clustering (K-Means on Big Data Features)

$$\min_{C} \sum_{i=1}^{k} \sum_{\mathbf{x} \in C_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2$$

- C_i: Cluster i of clients
- $\mathbf{x}$: Big-data feature vector (e.g., spending, demographics, goals)
- $\boldsymbol{\mu}_i$: Centroid of cluster i

3.1. Definition and Characteristics

Artificial intelligence (AI) refers to the capabilities/task-solution state and processes that replicate/improve the individual intelligence, collective intelligence, and decision-making intelligence of the natural and human systems or their characteristics and principles. Intelligence can be categorized in different ways: (1) capability/task types: mathematical and logical intelligence, language intelligence, sound and visual intelligence, robotic intelligence, and collective intelligence; (2) modeling perspective: model-driven and data-driven intelligence; (3) knowledge representation: explicit, implicit, and hybrid (explicit and implicit) knowledge; and (4) involved knowledge shape/language: graphical, relational, mathematical, statistical, rule-based, semantic, and hybrid-based reasoning. Big data refers to the huge amount of naturally/automatically harvested data, large data-driven knowledge bases, and data pools involving more than a million instances/entries, rows/records, relations, and parameters/edges. A proper taxonomy/schema and framework to characterize and summarize different big data is expected to take (other) classical data/knowledge types into consideration. From the perspective of characteristic parameters, type, size/scale, dimensionality, granularity, data source, accessibility, content/domain, and language should be considered. Data needs to be stored in proper storage/containers/forms for effective data access. Data persistence, accessibility, quantity, format, structure, semantics, and noise also need to be tackled for big data acquisition, transformation, and preprocessing. The key techniques/tools of database and data warehousing, peer-to-peer (P2P) data publishing/searching/exchanging, data integration/cleaning/mining, data visualization, data/frequent itemset/association rule/classification/regression/cluster pattern/discovery, time/dynamic-cross/static pattern discovery, NLP, semantic web/searching, and (distributed) data mining/ visualization refer to different data synthesis and service tasks. Financial technology (FinTech) refers to the financial-sectorly smart systems that facilitate financial market/service innovations and smart financial systems and practices by: (1) analyzing, managing, optimizing regional/planetary financial system networks, their working mechanisms, drivers/benefits/harmful effects, and cooperative/malicious behaviors at the regional/planetary level, transaction-based financial networks, trading mechanisms and their cooperative and malicious behaviors, execution, settlement, and pricing mechanisms of digital economies, and new customer/service-scheme matching/ optimizing mechanisms along with investments, financing, consumption and service, with deep-data basis and first-principle models; (2) smart financial knowledge/ assistance/credit tools/applications/systems in wealth allocation, finance, investment, trading, insurance, crowdfunding, auditing, assessment, financing, reputation, trust, privacy, anti-money laundering, cyberattack, and economic/ financial big data/data-intensive AI emulations/insights/discoveries with data-driven bases and simple structures; and (3) intelligent/efficient financial markets/ services by integrating AI, computer/ quantum/special-hardware/complex-networks technologies along with FoV society backgrounds.

3.2 Sources of Big Data

The large scale high speed datasets generated in knowledge acquisition, transfer, and servicing by commercial banking corporations, investment banks, insurance companies, and credit rating firms are termed big data banks in financial markets. The three vital private big data banks deemed in this study are. Additionally, several sizable private financial databases, such as , also serve as big databases of stocks, bonds, derivatives, IPO underwriting, and M&As. These commercial players, on the whole, compost large scale historic knowledge bases that cross connect with hundreds of funds. Clientele nearly always periodically pays corresponding fees to access the data banks that remain stored in the commercial players' marketplaces. Errors in the big data banks used in financial technology are inescapable and remain highly stable.

Moreover, the private and public regulatory institutions in the financial industry and related areas collect large datasets to control and monitor firms. These datasets compiled independently in each region are contracted to the latter only. In general, the big databases gathered by private regulators are composed of firmindex ratio datasets collected from different local markets, such as, and Two important public databases assembled by the US and European regulators are and, respectively. The latter only data banks of regulators are often amalgamated with the private databases of commercial players.

3.3. Data Processing Techniques

This section surveys incumbent techniques of AI with an extensive overview of classic FinTech centered on big data. Research opportunities and challenges are also identified in both data and model processing techniques for big data finance. As terrifying as atomic and nuclear consciousness, deep finance is an elegant yet dangerous means. It is extensive AI, especially deep learning in finance. AI techniques for analytics have great potential to handle finance's big data and develop more sophisticated models for challenging finance problems. Modern AI techniques hold great promise and challenges for the industry, academia, and society, and may impact financial practices, economy, and society as atomics or nuclear physics. It is also essential to deeply understand the characteristics, issues, and challenges of finance to synthetically deepen the understanding, principles, and values of potential use and misuse of AI approaches in finance.

Finance has always been interested in intelligent techniques and tools, regardless of the flexibility and sophistication of the tools. Improving tools while having an elegant understanding of modeled entities or processes may be powerful. However, deep finance poses severe challenges: unfriendliness, mis-interpretability, instability, and complicatedness of AI analysis approaches. Financial research and socio-economic stability, safety, or sustainability may also be challenged. It is urgent and critical to synthetically deeply investigate deep finance from academic and environmental, industry, economic and social, and ethical perspectives. Finance has incited many burgeoning interdisciplinary research tasks with new phenomena. AI techniques, especially modern techniques, hold great potential for finance. However, it is substantially different from conventional and industrial finance. The AI-finance interdisciplinary research is in an academic tumultuous space, which can be an opportunity for diligent scholars and practitioners, especially for profound multidisciplinary intelligence.

4. Investment Strategies Enhanced by AI

Artificial intelligence (AI) in the financial sector is a fast-growing area of activity. The availability of data, advancements in machine learning algorithms, and affordable and scalable computing made it possible to create competitive AI solutions at a reasonable cost. Investments in AI technologies have multiplied, and big players are undertaking actions to grab the advantage. Given the wide spectrum of AI applications, it remains to be seen which AI applications will prevail in the financials and which will be neglected in the long run. This research examines AI applications used by hedge funds and analyzes the advantages and disadvantages of AI investments concerning traditional rules-based approaches. The research is based on the systematic analysis of academic works and AI projects/solutions offered by firms worldwide. First, AI applications are outlined and compared to the commonly used rules-based approaches and other non-AI models. Each set of AI application benefits and pitfalls is addressed with concrete examples from academia and industry. Subsequently, the practical implications of findings for hedge funds' investment strategies are discussed.

AI has become an essential part of many investment strategies over the last few years. Its applications in the investment setting go beyond the traditional quantitative finance field and involve innovative areas such as natural language processing (NLP). Current AI methods are a powerful tool for discovering exploitable patterns in asset price movements from various data sources unavailable to fund managers. The data explosion has multiplied the number of trading strategies used by hedge funds and algorithmic trading desks. When employed successfully, diverse strategies can increase the asset universe in which a fund can effectively operate and provide opportunities for alternative investment exposures to the investor. Nevertheless, there are several pitfalls to using AI in investment strategies, stemming mostly from data questions, regulatory challenges, and noisy output produced by many current AI algorithms.

Some examples of ball pitch detection using computer vision and AI applications in finance. Self-driving cars and street surveillance systems rely on fast data acquisition and immediate processing from multiple cameras. The history of market price forecasting and trading goes back many decades and has been studied with various approaches. But similar to the case with self-driving cars, financial markets are usually noisy and chaotic with a partially or fully unknown structure. Consequently, price movements are stochastic, and regimen detection is often wasted. Even if it seems impossible to predict market prices, pattern recognition of particular patterns and events occur frequently.

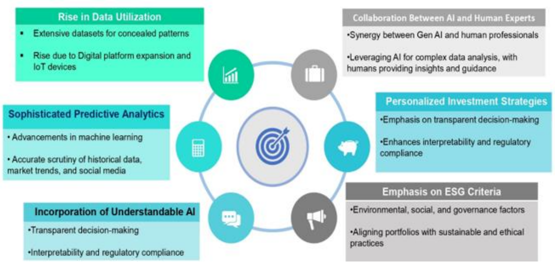

Figure 3: Investment Strategies

4.1 Algorithmic Trading

With the rapid development and maturity of fintech, algorithmic trading has played a central role in finance. The combination of computer programs and mathematical control methods aiming at deciding stock, foreign exchange, and crypto asset trading strategies has attracted the attention of finance researchers and practitioners. In the post-COVID-19 period, major stock indices dropped dramatically in a short period of time. Market falls were observed in parallel across all assets across the entire world. Data-driven algorithmic trading to reduce the risk of volatility in such extreme events is required in such a market.

However, designing, programming, comparing, and evaluating the trading strategy are challenging. This study propounds a pipeline for the research on algorithmic trading for both stock and crypto assets, in terms of data collecting, feature engineering and selection, programming, quality control, back-testing, and classical algorithms. A trading strategy is generally designed for one specific market. Therefore, very few studies have focused on both the conventional financial market and cryptocurrency market together. This may be a significant gap in terms of a comparative study between traditional finance and crypto-economics. In this paper, a comprehensive approach covering the full pipeline of algorithmic trading design and evaluation. This pipeline was implemented through object-oriented programming for the Python language, offering open-source software for academic research and practice. As major stock indices are dropping in a short period of time in the post-COVID-19 period, it is even required to do data-driven algorithmic trading to decrease the risk of volatility in such an extreme market globally. Various means could be used to investigate the risk of volatility, such as function and icon filtration on original time series, technical analysis, macro-economic factor, and sentiment analysis.

4.2 Predictive Analytics

Predictive Analytics enhance decision-making processes and provide valuable insights on large-scale datasets. Thus, predictive analytics are essential for sectors where understanding forecasting is essential. In several fields, predictive analytics is becoming increasingly popular such as manufacturing, transportation, finance, communications, and business. Predictive analytics tools can provide forecasting solutions like risk management, asset pricing, stock returns, and market efficiency. Predictive analytics can be classified into three categories: descriptive analytics methods, classification and regression analytics methods, and future event analysis methods.

The major components of predictive analytics (PA) are data, algorithm, technology, and user. Multiple entities generate data and store it in heterogeneous storage spaces in a complex network. To enhance business processes, various types of PA tools analyze transactions and learn their patterns. Data science teams perform high-level analyses on past, present, and near-future events and present them in personalized dashboards. Subsequently, user departments implement the supplied data observatories to address identified weak points. This paper extensively searches the existing literature through the state-of-the-art framework and pinpoints future research directions. The provided detailed proactive reviews on the existing knowledge can benefit researchers and practitioners in deploying more efficient and effective future research. Furthermore, providing the first formal review on paper is expected to set a groundwork for more relevant comparative reviews. PA components and categories in depth Support Vector Machine and ensemble methods can cope with asymmetric data globally and locally and address imbalanced classification problems. In info-theory based assessments, well-designed feature extraction tracks can be detected, and new feature characteristic patterns can be learned.

4.3 Risk Management

An accelerating digital transformation across industries which was initiated by the COVID-19 pandemic is the root cause of significant changes in societies including economic systems, company organisation, and individual behaviour. Digitalisation enhances approaches to consumer selection and reach, and business model development and realisation. Consumer behaviour has been enhanced and altered as well, indicated by exponential increases in the number of online searches, online platform usage, and in the volume of online and mobile transactions. The substantial changes have by all means impact companies and the finance industry as an economic sector. After the digitalisation wave swept companies to redefine business models, the financial services sector is the next that has to face fundamental changes. They are pressed by new alternatives to traditional and established services, the rise of cross-industry competition, and by increasing bias to access low-cost services and applications. Most importantly, they are facing the paramount task to provide better services while reducing costs. The biggest grip on services, core competencies, and business models consequently weakens control over data. Data is crucial, the new fuel, as machine learning techniques to predict what previously could not be known on the basis of data have spread across industries. Managing risk remains to be the most important and omnipresent competence in finance.

The overall goal is to provide risk measures, limits, and data and model control functions. Three novel ideas critical to the functioning of the risk management framework. First, Risk service-based architecture of risk measurement provides all risk services, risk reports, and data and model controls to all users in a uniform and consistent way. Second, a new hierarchical representation of risk measure time series for risk limits encapsulating information on risk limits and its breaches. The hierarchical representation of risk measures leads to easier interpretation and faster quality assurance of risk limits by all stakeholders. Third, a model suite representing the bank's exposures and their risk propagation amounting to a billion FLOPS. The Deep Asset Liability Management framework targets the whole term structure of AT1 callable bonds. It aims at managing the asset and liability sides of a financial entity simultaneously subject to domain-specific constraints. A stochastic control problem derived from the risk-neutral framework, where both sides are specified as Multi-Layer Perceptrons. Deep neural networks approximate the value function, the optimal exercise boundary, and the optimal control of the asset procurement strategy. Computational challenges concerning a high number of inputs and dimensions are addressed by a dedicated multi-fidelity Monte Carlo algorithm.

5. Client Insights through Big Data

For banking institutions, a content marketing strategy should be used in branded banking communication. Also, choosing traditional vs. modern media should rely on past experience with certain media and the risks assumed with respect to compliance in modern media. Emerging technologies should be used by banking institutions, to a greater extent than is currently the case, for attracting new customers. In devotion to marketing strategy, bank officials should know where bank marketing is heading and also how a marketing effort should be monitored. The advent of big data has caused a major shift in how organizations approach data collection and analysis. Technology is rapidly becoming part of society, influencing the way we live and think about ourselves and our identity. Banking institutions constantly rotate between understanding their customers and applying this knowledge to achieve competitive advantage, provoking a cycle of banks being competitive and the outlook for banking innovation being revolutionary with guaranteed and superior commercial success. Understanding customers is good for banking institutions, providing them with insights into customer behavior and preferences, allowing them to anticipate their needs and redirect investments in the appropriate way. Both customer and institutional behavior and preferences have changed markedly over the past decade. Banking institutions were obliged to provide operational solutions to new possibilities of choice, access, and price. The infrastructure was dramatically altered to accommodate dispersed computational and communication power and bandwidth. Bank marketing analytics have also changed in focus and methodology, and usage of traditional promotional methods has been on the decline. The purpose of this paper is to contribute to the understanding of how data sets are analyzed by banks. Banking institutions possess priceless proprietary behavioral data sets about what has happened on the market. Big data is all around, providing an unprecedented opportunity to understand customer behavior and preferences with a timely and nuanced understanding of their sensitivity. However, customers are careful regarding personal data retention run on the net, foreseeing the opportunity of targeted promotions, data leaks, and purchasers. A timely understanding of the market of a client would provide sharp insights into modification of account offerings and price. However, demographic features denote coarse segments and introduce the potential for discrimination against consumers. Recently, advancements in representation learning have taken root across industries, providing a new paradigm for utilizing AI in wide-ranging applications. The redundancy of such data arises as intensive data capture often exceeds a firm's capacity to effectively collect and process it. As a consequence, organizations struggle to separately identify significant information within the noise of irrelevant data, with potentially detrimental effects on risks, reputations, finances, and market positions. The goal is to provide an opportunity for AI researchers and practitioners to showcase their ideas and approaches to regulation bodies.

Equ: 3 Robo-Advisory Decision Rule (AI-Driven Allocation Function)

$$\mathbf{w}_t = f_{AI}(\boldsymbol{x}_t, \boldsymbol{g}_t, \theta)$$

- $\mathbf{w}_t$: Recommended asset allocation
- $\boldsymbol{x}_t$: Current market state (macroeconomic indicators, volatility, etc.)
- $\boldsymbol{g}_t$: Client goals/preferences (e.g., risk tolerance, horizon)
- θ: AI model parameters (trained on historical investor behavior)

5.1 Customer Segmentation

Customer segmentation is an important field in banking. Customer segmentation has typically been achieved using demographics such as age, gender, location, etc. However, these features produce coarse segments and introduce the potential for discrimination. Micro-segmentation provides a more sophisticated classification that improves personalization and promotes fairness. Artificial intelligence is becoming ubiquitous across industries with representation learning an auspicious method for customer micro-segmentation. Sensitive industries such as finance face legal and ethical obligations towards responsible implementation of AI. Explainability and interpretability are key elements in responsible AI, which are generally not adequately addressed in applications of AI in finance. The aim is to extract and facilitate the use of salient features in future financial services; the ultimate goal is the development of personalized financial services in which responsible customer micro-segmentation is key. Integrated banking systems have an increasing volume of various data streams generated by customers, allowing institutions to observe behaviors in real-time. Consequently, it is now possible to analyze such data to gain insights into behaviors and detect patterns that previously could not be seen. Customer segmentation is the process of dividing customers into groups. Segmentation is important, as the banks would like to provide exactly what their customers desire. Segmentation traditionally has been achieved using demographic factors such as age, gender, and location.

5.2 Behavioral Analysis

Behavioral analysis in finance is a crucial aspect that aims to understand and predict investor behavior using past market data and sentiment analysis from news and tweets. Among various behavioral factors, loss aversion and the disposition effect have gained popularity in modeling behavioral finance. However, due to difficulties in obtaining historical data for long periods, few attempts focus on the behavioral analysis of analysts' ratings using NLP techniques. In addition, while investors' behavioral factors have been partially investigated, it is demanded to further analyze the series of conditions under which the behavioral factors occurred.

The financial sector, with frequent volatility in the U.S. market and the need to shrink losses during crashes, has had rapid growth in finance, fintech, and robo-advisors. Aimed at improving individuals' investment performance and portfolio management, various techniques are developed to build robo-advisors for personal and wealth management. However, attempts at behavioral analysis and intelligent guidance for financial planners using NLP techniques are few. Financial planners provide investment advice for clients to increase the chance of meeting their financial goals. On the other hand, financial markets are inherently uncertain and constantly volatile, and past price actions are likely to repeat themselves. In addition, whether one holds an asset and asset classes may be affected by peers' influence. Analyzing the advisors' financial summaries using NLP techniques helps predict the investors' needs and give proactively intelligent guidance for financial advisors to coach clients during adversarial market conditions.

In analyzing the summarized writings of advisors, various types of behavioral factors are extracted, including loss aversion, questioning of evaluator, and the descriptions of avoidable assets. A time-series behavioral text analysis algorithm is provided to validate the existence of loss aversion for investors adopting long investment horizons. Regression models are also built between these behavioral factors and the past two trading days' market changes to find the types of behavioral factors with high im-predictability for time-series behavioral analysis. Then, for actively analyzing an individual summary, various sentiment scores of market comparison between the DJIA index and stock price, seven behavioral factors, and two past price changes over the past two trading days are hierarchically fed to an extreme gradient boosting model that predicts time-series behavioral factors.

5.3 Personalized Financial Services

Along with the impact of big data technologies, artificial intelligence (AI) is changing the landscape of services by developing new service delivery channels, self-service applications, and advanced analytics. These developments have impacted complicated fields of services, including financial services. The digital revolution is reshaping the traditional business environment in banking, asset management, and insurance. The term Financial Technologies (FinTech) has emerged from the accelerating development of technology in order to cope with, disrupt, or in some cases even keep up with the rapid digitisation of financial services and financial functions. FinTech encompasses a wide number of challenges. In a broader sense, the joint terms describe technology and innovation that aim to compete with traditional financial methods in the delivery of financial services. Some key trends include peer-to-peer lending, crowdfunding, payment innovation, personal finance, and digital currencies. AI applications in financial services include credit decisions, risk management and control, fraud prevention, trading, estimation of operation results, and even the detection of money laundering and matching transactions between customers and investors, as well as customer data, address verification, scoring, and on-boarding (acceptable customers). In traditional banking, pricing of products and services on the retail side, including loans, mortgages, deposits, and other products, as well as on the asset side, considering stock price predictions, fuel prices, option or future price predictions, just to list a few, mainly rely on chosen econometric methods and models.

Figure 4: Personalization in Financial Services

6. Integration of AI and Big Data in Wealth Management

The finance industry has long suffered from information asymmetry, while access to finance has been monopolized by a few large companies. With the advent of the Internet and the boom of big data, it has become possible to better integrate long-tail markets by comprehensively collecting and analyzing diversified data through the Internet. This data can be converted into prior knowledge, partnered with AI technology, and served globally. Customers' on- and off-line behaviors, payment records, supply chain relationships, and public finance and consumption-related data can be processed in compliance with regulations, creating a 360-degree global and thorough record for individuals and firms alike. Applying state-of-the-art AI technology to these data can help effectively understand customers to reconstruct credit ratings for on- and off-line risks. Funds can thus make comprehensive and intelligent decisions regarding credit extension or wealth management with clear insights into customers' preferences and risk tolerance.

It is now possible to build a much more reliable, universal, and low-cost credit assessment technology, which in turn significantly lowers the financial threshold, thus improving services. Specifically, instead of obtaining the credit rating by understanding the credit record from credit companies, the rating can be built via knowledge graph technology to integrate diversification and evolve prornotally. These records also contain wealth management needs, while the assets to be managed come from all walks of life. The current means include filtration tools for searching information on new financial products with a pressing need for professional awareness of market conditions, Rozo-Advisors for managing portfolios based on algorithms but lacking consideration of global finance knowledge, matching tools for recommending products with credit ratings, and automated transactions to enhance returns. These high-frequency and tedious tasks are also suitable for machines to do.

The rapid growth of personal wealth and high-quality financial product supply has led to the recent emergence of needs for asset management service for individuals. The early services focus on processing existing portfolios, while there are now extensive needs to maintain and even enhance returns with an adjustment of or plans for holding products. Wealth managers can help access professional knowledge to process investments, so that risks can be mitigated and profit margins enhanced. However, the inefficiency of human labor in times of rapid growth and the limitation of the number of firms increase competition and reduce profits. Additionally, wealth managers have limited access to all data sources and thus cannot trace individual and institution behaviors globally, acting as overseers of on- and off-line investment, trading, and wealth changes. Partnering with AI technology and big data, four key tasks can thus be addressed to provide enhanced wealth-management services: characterize customers, predict investment targets, model customized recommendations, and back-testing and regulating.

6.1 Technological Infrastructure

Technological infrastructures of big data and artificial intelligence (AI) in services tremendously affect sensitivity and accessibility of sophisticated management, decision-making, and risk evaluation so that precious value of customer data can be potentially harvested. Basic structure of financial-action ADCs, applied scenarios of AI and Deep Learning models in stock price prediction and credit evaluation are introduced, and development of a self-contained FinBrain ecosystem is presented to illustrate the integration between finance and AI. At the forefront, it is the customer who eventually drives the sophisticated infrastructure to improve accessibility and sensitivity. Credit risk assessment revolves around the fairness of credit scoring, and availability of credit development occurs at the expense of model performance, fairness, and intuitiveness. Especially on the rougher edge of the financial market, there lies tremendous unaccounted value due to difficulty of authorization and compliance as well as sparsity of historical trading records, which has consequently triggered great attention toward lending via alternative sources of information such as natural text and social relations. Despite the springing of customer-driven private-equity-financed initial coin offerings, the inappropriate and inaccurate use of data could lead to huge wastes of resource both monetarily and socially.

In the financial market, exigent demand for sensitivity has recently arisen as speculation on crypto-assets abruptly surged. Sophisticated models which are extensible to various strategies, indicators, and assets are needed not only for professional traders and investment institutions but also for retail investors with diminished tolerance toward systematic risk and human misdeed. Similarly, the accessibility of management tools and services would be helpful as the consequences of missing trading opportunities can be more painful when confronting high-frequency traders. Integration of long-tail markets that have less comprehensive coverage and more individualistic trading styles can improve the efficiency of fund allocation and mitigate more risks. The basis of product diverse management, and information-integrated management lies in AI-supported fine-grained customer description, mobility detection, and opportunity tree discovery.

6.2. Data Governance and Ethics

Unprecedented volumes of data have been generated by the digitization of the economy and society. In this context, Big Data and artificial intelligence (AI) techniques have emerged to extract insights and generate decisions from such vast data. However, alongside the unprecedented opportunities, this also poses critical challenges that could damage the economic and societal fabric. To account for the ethical challenges posed by this development, the concept of ethics has received prominent attention across the disciplines. This concept comes with a rich variety of connotations and interpretations, leading to hotly debated questions referred to as the ethics of ethics. This entry investigates the ethics challenges of Big Data and AI through the lens of AI and Big Data analytics in health insurance.

Big Data principally denotes a socio-technical phenomenon: a societal data deluge coupled with technical capacities to harness the data into a plethora of processes, products, and decisions. Therefore, Big Data is necessarily a combination of data, infrastructure, and litigation. Although being chronologically prior, 'Big Data' is commonly viewed as a broader concept, whereas 'AI' is a subfield of Big Data. AI refers to decision-generating computational mechanisms with generality and automation, which has become extensive throughout a wide variety of economic sectors and societal industries, including healthcare, public services, education, finance, manufacturing, science, and agriculture. On the positive side, this development could (i) assist human intuition and amplify human capacities; (ii) highlight novel knowledge and inform human decision-making; (iii) enhance operational efficiencies and stimulate innovation, as well as (iv) result in enjoyable applications and elevate persons' quality of living.

On the negative side, these techniques could (i) aggravate inequality and prejudice; (ii) bring socio-technical blindness and upheaval; (iii) undermine user rights and kick off undesirable emergencies, as well as (iv) increase trust, privacy, and security concerns. In sum, AI and Big Data analytics generate significant socio-ethical changes and economic and societal effects, satisfying the criteria for a social phenomenon worthy of normative deliberation – the so-called ethics of Big Data. In response, a small but growing effort has been devoted to ethical scrutiny and reflection on Big Data per se. Specifically, the ethics of Big Data concerns the balance between economic benefits as well as ethical questions posed by Big Data from a fundamental perspective. This discourse goes back to the well-known ethical principles of the EU and OECD.

Figure 5: Data Governance and Ethics

6.3. Case Studies of Successful Implementations

The use of big data and intelligent tools has transformed investment management as well as asset pricing techniques. While the goal of traditional finance research was to identify market anomalies and develop market-neutral strategies, the vast information provided by big data has led market players to abandon the principle of the efficient market hypothesis. Since the competition among agents in analyzing market data has become tremendous, agents rely on an increasing amount of high-frequency stream information. Both the macroeconomic information and low-frequency data on GDP and employment are collected from various sources and exploited in text analysis in hopes to predict the short-term/medium-term price movements.

Their expected changes in the policies of the Federal Reserve have provided an early signal of the movement of the U.S. Treasury bond prices. utilized sentiment values from social media, blogs, and news in a short-term strategy. Their prices shot up for some firms and drop for others after the earnings announcement was predicted. Text analysis also plays an important role in tweet-to-price strategies. Sadoulet and Tieman discovered the long-term relation between the average tweet sentiment and average daily price return. Text mining methods have also been applied in fundamental analysis or corporate event-driven approaches.

As a broader umbrella, all the phenomena researchers are trying to investigate and analyze are expressions revealing the beliefs or behaviors of traders, and the main measurement of such activities is the change in price. Meanwhile, conventional finance models have been widely criticized and abandoned. Data-driven and statistical methods have captured a broad set of market patterns and behaviours. The research on quantum finance is still in its infancy. On one hand, this framework is promising since quantum computers have the potential advantage of exponentially higher capacity to store information and decode, faster information update, noise robustness, low-degree entanglement for matrix commutation, etc. Research on quantum-book can be constantly conducted while waiting for a feasible physical quantum computer.

7. Challenges and Risks

As the examples from earlier chapters have shown, implementation of artificial intelligence algorithms and big data solutions in investment management is difficult. Investment markets are complex and dynamic, hence all involved parties have to constantly adapt to changing conditions in everyday practice. Nevertheless, unstructured data, for example news data, social media data, and all kinds of documents, however remain unexploited by alpha generating algorithms. Still, relevant AI algorithms, such as natural language processing, reinforcement learning were not explored yet in this area.

Investment management companies are data rich but information poor. Various structured and unstructured data sources are available today but huge amounts of investment insights rely on human interpretation. The industry should embrace data science as well as innovative big data and AI algorithms currently being applied in other business sectors. The investment management industry should leverage similar human capital, analytics and technologies to improve investing results.

Implementation barriers are numerous. Notorious tech talent shortage remains. On the data side, firms are often plagued with siloed data, limited access to data, and messy datasets. A study surveying over 100 financial data scientists showed that 96% find unclean datasets as a top barrier for accurate model results, while the second biggest pain point (76%) relate to lengthy data acquisition processes. Top financial firms have set to embrace data democratization; cloud, big data solutions, and agile processes are necessary for moving the firm towards an analytics-driven organization. Streamlining data and collaborating with startups to gain access to big data, innovative algorithms, and tech talent is to be prioritized based on firm capabilities and mission. Nevertheless, high competition in the financial services sector makes execution of such a strategy difficult since many firms are exploring similar algorithms and data.

Two pervasive risks are identified and discussed. The first risk relates to model risk, resulting from insufficient belief on predictive performance or changing circumstances such that pre-emptive model management would be necessary. The second risk relates to reputational risk of data used in AI applications, for example, the scrutiny raised if users' fed data or previous trades were not fully implied in a recommendation engine.

7.1 Data Privacy Concerns

Gaining new information that has never been in the possession of an individual can lead to privacy concerns. Individuals are unaware of what information will be gained by other parties and how behavioral models will be influenced. Many businesses rely on data spread in the environment; however, there are still only little regulations governing the processing of data. Individuals are often not aware that information is exchanged or how their privacy will be affected. Nevertheless, regulations permissibly focus on two aspects regarding the privacy of data: 1) informed consent and 2) anonymization. Informed consent means that privacy intrusions are permitted when a person has authorized a party in charge to receive their information. Even though it is not doubtless whether individuals ever provide such an express permission, numerous regulations to protect privacy contain provisions on it. An increase in the proportion of documentation and information involved and part of informed consent has become necessary, because consent is deemed unconsciously given at the moment of sharing the document. Additionally, anonymization aims to make the data no longer personally attributable to the individual. As of today, it is, of course, not possible to reconstruct a p and generate the information used in an innovative application not open to ones prior. This was the essence of the term "anonymity". Nevertheless, it is often undisputed how about it still remains possible to get close to the true answer p′ of c using Attribution켜 며. Surprising applications combining database systems and predictive analytics yield spectacular reputations when, for instance, they report such information. At least those matters are: When a business cannot sufficiently

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anonymize the data of its customer, it will have little to offer to regulators on that data after receiving a fine. When businesses learn how to combine different sources of information and via which channels the information and its consequences leak, it will be next to impossible to flag the existing parts of the information system. As a result, there is reason to believe that privacy protection measures today take mediation efforts that will not be efficient in the future: Current measures will not work in next years when 2020 ends.

To curb learning from private data, a new privacy-preserving paradigm is needed. A good starting point for a new research direction could be to investigate the incorporation of existing privacy protection techniques producing synthetic versions of sensitive data or anonymizing them into neural models. The creation of generative neural networks has recently become a more mature field, being used to generate setups of all kinds ranging from black and white images of handwritten numbers through fake images of celebrities to soft synthetic voices that anybody can impersonate. There are also preliminary works about training GANs on sensitive healthcare data and re-using them to train deep learning models on synthetic samples under a privacy proxy model. Additionally, federated learning, which uses model parameters instead of sending data, is also a well-established area that could be considered. A neural network could generate synthetic data from sensitive inputs, or federated learning could allow clients to train a central model without sharing their data. As an important concern, approaches based on "decrypting" prior perturbations should be avoided, as injected randomness and encoding could not guarantee privacy in such a case.

7.2 Algorithmic Bias

The need to ensure trustworthy AI has become urgent for organizations deploying algorithmic systems in high-stakes decision-making. Algorithmic trustworthiness has a variety of facets. A crucial one is algorithmic fairness. A fair algorithm produces predictions that are not biased against any group, but this potential is hampered by algorithmic bias. Algorithmic bias arises from a combination of data, models, and the training process. Groups of individuals whose predictions are disproportionately affected have been identified in various domains, including credit risk assessment in finance, hiring in HR tools, and criminal risk assessment . While there is ongoing research into model choice, training procedures, and how these biases might be mitigated, most commercial algorithmic systems remain opaque black boxes. It is thus hard for stakeholders to ascertain whether deployed systems are biased and to what degree. Understanding and exploiting model and data interactivity can aid in this regard. Algorithmic fairness research focuses on the algorithmic aspects of fairness while taking dataset bias, as the source of unfair predictions, as given (model choice experts would question the logic of such exclusion). Data bias and unfairness usually interact. Such interactions and their implications are unexplored.

There is no consensus regarding the definitions of bias and unfairness between these concepts. Bias is described as a qualitative attribute of predictions. In this sense, a fair model can be biased if one of the populations is worse off than they would have had a different, and fairer, model been used. Bias originates in either data, models, or the training process. Bias in one component may incur bias elsewhere in a pipeline. The significance of data and modeling bias in the production of unfair predictions has been a prominent research question. Machine-learning fairness research mostly focuses on how to detect and mitigate unfairness produced by a learned model. Despite calls for a unified understanding of what constitutes biased data, vast streams of literature produce differing proposal sets. When there is societal ground truth or when differences between populations are known, automated bias detection processes can compare data distributions to detect self-disclosing bias.

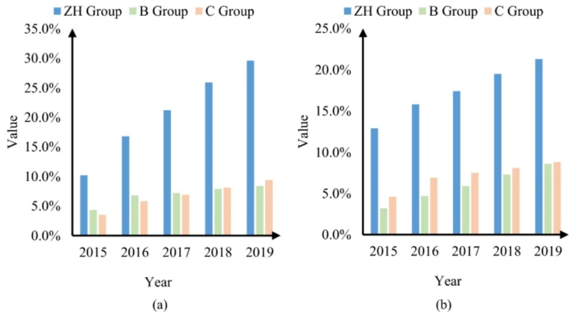

Figure 6: Financial big data management and intelligence based on computer intelligent algorithm

7.3. Regulatory Compliance

With the fast adoption of big data and AI (BDAI) in finance, banks and vendors are ramping up efforts to address the regulatory, operational, and reputational risks and ethical concerns that arise. Concerns include data privacy, explainability/fairness concerns, and the systemic nature of BDAI-driven models. Regulators both at national and international levels have been increasingly focusing on this space. Against this backdrop, this paper presents a systematic review of current regulatory and supervisory frameworks, principles, guidelines, and expectations that address BDAI adoption in financial institutions.

A diverse range of public BDAI regulations, guidelines on model risk management, and supervisory expectations are found, illustrating a major gap in addressing BDAI risks in banking-specific and comprehensive ways. Specific topics mentioned in existing frameworks and regulations, such as data privacy and algorithmic transparency, are triggered from the general BDAI regulations and guidelines. Current regulations primarily address potential risks from the data supply perspective instead of specific models and adoption. Given that various BDAI strategies could be pursued in practice, this revealed state of BDAI regulations in banking gives insight into scope expansion for banking-specific BDAI regulations in the future.

Advances in artificial intelligence (AI) technologies have motivated substantial adoption in financial services, particularly in the banking industry. The significance of an adaptable and dynamic enterprise risk management framework in addressing AI model risk has emerged. Financial services apply AI models in processes that span customer engagement, product development, marketing, and risk management. The range of AI model types includes decisions made using AI algorithms, as well as decisions informed by AI recommendations or probabilities. Banking regulators have issued guidance orienting banks towards model risk governance practices that address bias and other AI risk concerns.

However, governance practices identified in research often struggle with these fundamental differences in AI characteristics, as well as between different financial services sectors. Even sophisticated banks implementing governance across multiple jurisdictions and lines of business could face challenges in conforming with widely varying regulatory expectations around AI model risk management. Current governance interfaces rely heavily on manual steps with many niche applications, creating operational scalability challenges for governing AI models. The need for comprehensive solutions to govern AI models that address a wide array of predictive tasks emerges as a key undertaking for the financial services industry.

8. Future Trends in AI and Big Data in Finance

AI (including machine learning and deep learning) and big data (including small and large volume data) continue to usher in a digital revolution in financial technology (FinTech) and fundamentally reshape the finance industry. The digitized financial industry, such as the multi-markets of stock, bond, foreign exchange, derivative, alternative, and cryptocurrency, connected by deep networks, timely signals, and widespread communication channels, is coupled with many financial pricing, risk, prediction, and regulation issues.

Cross-big and interconnected data from multiple markets, signals, platforms, and domains blend in the finance industry. The cross-space deep understanding, interpretation, and modeling of the interconnected finance industry become significant but challenging. Multi-market applications include effective mix-in modeling of multi-market financial pricing in stock, mutual fund, and cryptocurrency markets and a coupled modeling of outlier detection in multi-market insider trade and fraud behaviors across stock, borrow, and share loan markets. Multi-signals include simultaneous cross market capital regime modeling with a big mix of social media, textual, and quoting signals. Multi-platforms include compelling model and regulation compliance modeling for market abuse detection across trading floors, marketplaces, and dealing desks. Multi-domain applications relate to model and risk assessment of digitalized financial businesses and banks with a deep multidimensional understanding of complex networks, nodes, and characteristics.

Despite intensifying coupling, these complex behaviors are traditionally modeled in isolation within a market, signal, platform, or domain. Each of the deep understanding and modeling is challenging in and of itself. With increased coupling, the challenges intensify and become exceedingly complex, and often lead to new questions and risks to be analyzed. Collective modeling and understanding of coupled complex behaviors are desired with concepts and technologies from complex systems that have been successfully applied in other disciplines. On the other hand, sophisticated and deep understanding is an unprecedented challenge in itself. Interactive yet adaptive models of the finance industry at different levels and close cooperation between disciplines and academics and industries are demanded. Recurrent and pondering questions in timeless and spaceless nature finance and pricing are worth further modeling investigation.

8.1 Emerging Technologies

Rapid advances in technology have led to increased complexity in the global system and the emergence of new financial instruments and significant technologies. Financial technology (FinTech) is financial services that incorporate cutting-edge technologies such as Artificial Intelligence (AI), Big Data, Digital Currency, and Blockchain, benefiting clients, customers, and companies. This technology is fast evolving due to its capacity to provide innovative solutions that meet the changing needs of consumers as e-commerce and internet usage have significantly expanded, opening new platforms and opportunities for players to enter this sector. At the same time, the increase in the number of market players has raised competition, leading to the introduction of several innovative technologies in the finance sector, including AI, big data, machine learning, automated technology, fintech, and blockchain. FinTech is the integration of technology into financial services, and AI is the simulation of human intelligence process by machines, especially computer systems, including machine vision, natural language processing, and robotics. Furthermore, in finance, FinTech is the shift from traditional paper-based financial systems to the digital-based data-driven financial systems due to extensive use of the digital platform.

Some emerging technologies and trends are anticipated to have a major influence on the financial services sector, including AI. The increasing demand for better data management capacity for precise analysis and forecasting and better speed of decision-making and execution has led to the widespread implementation of big data in capital markets. AI technology increases productivity, enhances customer satisfaction, and significantly lowers operational costs. Financial institutions can incorporate various AI-based applications in multiple domains. Risk management is seen as the biggest area of growth. AI can correlate an unprecedented volume and variety of data sets, allowing institutions to uncover previously hidden links between common practices and late-stage signals that might indicate imminent systemic risk. As a result, it is becoming increasingly feasible for regulators to monitor the stability of the financial system as a whole using AI. These systems can also improve scenario testing for stress tests and derivatives. Furthermore, using AI-powered predictive analytics in credit allocation enables banks to deliver product recommendations in real-time.

8.2 Market Predictions

One of the main applications of AI in finance is to study the market predictions domain in order to discover and extract actionable numerical or textual information from vast historical data. To predict a market's temporal behavior, AI techniques are studied on how well they used the raw historical data of index prices. More advanced AI frameworks that combine deep learning and mathematical models by switching dynamically epochs and active learning in the task of stock prediction are discussed in . The approaches can be distinguished based on how they adopt the historical data (current vs. historical information) and/or whether they analyze the co-movements of diverse sectors or indices for the prediction purpose (cross-sectional vs. single prediction). Due to the traveling time vectors of financial events, the traditional approaches based on fixed time-series or complicated temporal architectures for investigating only one company's prices typically do not perform well on the unstructured volatile data, which entail the TF method as the better choice of methods.

8.3 The Role of Human Advisors

Amid the rapidly growing AI sector, many firms are building or acquiring AI-augmented financial advisory software. FinTech firms acquire traditional financial advisory firms instead of establishing their own. Traditional firms will ultimately prevail and cooperate with developers to avoid or postpone regulatory scrutiny. Contingent regulatory changes will promote development of this rapidly emerging sector. A deep division of labor between advisors (strategic decisions) and developers (operational decisions) will likely arise. AI augmentation of the advisory process with improved data interpretation will likely become available sooner than fully autonomous advisory software. Augmented advisory software will shift the skills needed to advise and counter a likely rise in the fraction of customers with complex needs.

Investment advisory is a broad function, encompassing the provision of recommendations about portfolios of financial products coupled with an interpretation of how these recommendations accord with client profiles. Management of discretionary portfolios, where the advisor accepts full control over securities selection and execution from a client, is merely one part of a much broader activity. Robo-advisory is a form of digital wealth management delivering the advisory process online, generally in a mostly automated fashion. The advisory process is transformed by the use of AI systems and algorithms. AI-augmented advisory software takes control of pre-existing recommendations while traditional firms maintain final responsibility. Traditional firms take the lead in exploring horizontal integration and extend their capabilities either by acquiring existing FinTech firms or by developing a beta version of augmented advisory software.
Most existing firms cooperate with AI developers to prepare for competition as new entrants become better capitalized. Large traditional firms acquire mid-sized brokerage firms or partner with FinTechs. Upon completion, technological and regulatory advantages accrue to the acquirers. Current regulatory structures are based on financial service providers acting independently. If advisory and execution businesses coalesce, brokerage firms become the primary supervisory entity. AI-augmented advisory software is expected first in regions with low uptake of advisory services then higher in regions with higher advisory service uptake. Across historical contingency, a convergence towards augmentation of advisory software is expected bringing both new opportunities and challenges to advisory firms.

9. Conclusion

The development of the synthesis of AI and finance is to co-develop the side-aware good AI and finance to facilitate the Finance 2.0. It involves three layers: financial knowledge, synthetic algorithms, and real-world applications. An EcoFin competency framework with human-in-the-loop was advocated to advance AI and Finance in an interactive, progressive, systematic, and routine manner. The limited involvement of EcoFin theories and tools inspires new opportunities and a need to deepen the interdisciplinary understanding and knowledge of both AI and finance for smart FinTech synthesis. The knowledge gaps invite systematic, rigorous, and comprehensive eco-fin competence development via diversified FinTech syntheses. The AI and FinTech development positively correlates with the investment characteristics and the proximal market event risk levels. Cognitive learning pricing indicates inspired competition in the course of FinTech spawn, evolution, and condensation. Characteristics and temporal variations of AI/FinTech developable kinds, graduate maturity levels, impact greatness, and investor preferences are summarized. They present a foresighted implication towards FinTech investments. EcoFin behaviours modelling and prediction are critical for systemic risk mitigation in smart finance and smart economy in addition to good money flow. It encompasses complexity characterizing, interaction mining, risk appreciation, and impact prediction.

A conspicuous transfer of modelling and prediction from individual behaviours to systemic behaviours can overcome the data scarcity issue faced by systematic risk modelling/management, awarded with both academic and funding attention. Transform AI and finance and develop cross-disciplinary synthetic theories and tools for smart finance, economy and society. AI as a new universal method unfolds the new nature of finance beyond mathematical abstraction mainly in the past decades. The transforming intention and trends of finance are reviewed. Trading mechanism transformation and its consequences reveal the new landscape of finance. Blockchain technology revolutionizes the decentralization of financial transactions and business innovation and imperatively presents new opportunities and challenges for smart finance. Develop economic/financial problems-oriented AI theories and tools to specifically address economic/financial problems and their characteristics and complexities. Such problems are a subclass of computer science hard problems but exhibit distinct characteristics.

9.1 Future Trends

The historical development of FinTech is a major product of the transfer and transformation of information technology. After the birth of the internet in 1994, the Internet of Things (IoT) and blockchain technology emerged in the 2000s. The invention of big data and cloud technology during this decade greatly drew the attention of the financial industry. In 2015, AI technology dominated the world. The development of FinTech was most significantly based on new technology. The advent of each technology stimulated the rapid progress of the financial industry. However, the arrival of new technology enabled financial opportunities and risks at the same time. AI technology is currently the greatest concern in the financial industry. AI systems can replace or augment traditional financial services. In the financial service industry, knowledge workers account for the majority of the workforce. The competition in the financial industry is severe.

Traditional banks and securities companies have difficulty in halting customer reduction. All of the above-mentioned information technology has allowed tail-sized fraudulent trades to exist in the financial market. AI technology combined with big data can integrate long-tail markets and mitigate information asymmetry to improve the efficiency of fund allocation and financial risk management. However, related real-life use cases have not been explored. Meanwhile, these opportunities and challenges have in no way kept pace with the increasing enormity of the FinTech market and the escalating concern among governments and regulators. Financial stability has always been a key priority for the Bank of England. The importance of the sector as a whole and the operational interconnections between firms means that such developments raise broader macro-prudential questions. In recognition of these issues, central banks and regulators are engaging with FinTech companies to enhance their understanding of emerging financial stability risks. Banking is being reshaped by technology and new entrants are disrupting banking business models. During the World FinTech Festival 2020, it was noted that the pandemic has moved 5 years' worth of e-commerce growth into the past 5 months, along with an acceleration in the adoption of AI to better serve the virtually connected customers. The financial sector is an important field in which AI and FinTech can offer banks improved efficiency and greater cost effectiveness. AI has become an integral part of financial services such as customer support and trading optimization. AI in the retail banking sector has currently not been investigated or discussed deeply enough. Besides, banks currently use AI chatbots in market opening and cyber fraud detection. In the UK, banks such as Santander and HSBC have launched banking applications that employ voice recognition. The Royal Bank of Scotland (RBS) will roll out its "Luvo" AI customer service assistant. Bank of America, Capital One, Société Générale, and Swedbank have all been experimenting with chatbots. AI is the technology underpinning that.

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