Cloud-Powered Financial Intelligence: Integrating AI and Big Data for Smarter Wealth Management Solutions

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Article Info
Page Number: 16842 - 16862
Publication Issue:
Vol 71 No. 4(2022)

Abstract

Artificial intelligence (AI) is a cutting-edge technology that is revolutionizing industries by enhancing products and services with intelligent capabilities. AI has gradually entered the field of finance in recent years, which in turn has ignited a tech-driven financial intelligence (TI) boom. TI (also widely known as AI + Big Data in Finance) is drawing more and more attention from both academics and industry practitioners.

The capital market is dynamic and complex, both in structure and mechanism, which reveals enormous opportunities and challenges. Conventional financial services based on heuristics and experience can hardly meet the increasing demand for digital transformation of financial institutions. Especially after the scaled financial market turmoil events and the outburst of financial market fragments, the financial industry is facing great pressure in wealth management (WM), risk management (RM), financial consulting (FC), and so on. While the traditional financial institutions are struggling to autonomously improve service efficiency and reduce cost, financial intelligence with fast and accurate machine learning capability to handle complex data is gradually rising as a new paradigm of smart finance in the global wealth management market.

Financial intelligence, as both an academic and an industry concept, describes a wide range of rich topics on AI, big data, financial technology (FinTech), digital assets, electronic cash, and crypto-currency in the financial domain. There exist a number of surveys in this discipline, but they are either outdated and/or lack the extensive review of the technical literature, such as in-depth exploration of state-of-the-art techniques in TI. Additionally, most previous surveys contain only limited topics or single setups of the financial domain. To mitigate this academic and practical gap, this article aims to conduct a wide-ranging literature survey that provides both after-the-fact and forward-looking discussions on financial intelligence.

Keywords: Cloud Computing,Financial Intelligence,Wealth Management,Artificial Intelligence (AI),Big Data Analytics,Smart Investment Solutions,Predictive Analytics,Digital Wealth Platforms,Machine Learning,Financial Data Integration,Cloud-Based Finance,Robo-Advisors,Data-Driven Decisions,Portfolio Optimization,Fintech Innovation

Article Received: *24 January 2022*
Revised*: 26 sep 2022*
Accepted: *18 Oct2022*
Publication: *30 NOv 2022*

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1. Introduction

In the last few years, the development of Artificial Intelligence (AI) has accelerated in depth and breadth. A large number of AI products have sprung up. However, the application of AI in the domain of finance is lagging behind when compared with other fields. The capital and high-quality talents of the banking and finance industry have flowed to information technology firms which has resulted in a competitive advantage. Commercial banks need to make use of their existing advantages in transaction, marketing and a large number of customers to catch up the trend and improve their technological capabilities. Currently, three districts lack technical solutions where banks can catch up with technology equilibrium and improve mobilization efficiency: wealth management, financial products advertisement and customer service. The idea and key points of the solution of three districts are described in this essay. Among various definitions of AI, financial intelligence is a novel concept which comprises the investment prediction in finance and the understanding and explanation of the approach of financial professionals. Various innovative applications based on AI are also introduced along with their corresponding states, market and limitations to the understanding of the current state and level of financial intelligence. AI (Artificial Intelligence) is the core technology of the technology revolution and industrial transformation. Deep learning is the most important paradigm dramatically improving machine perception and cognition with an abundance of data in the big data era. Financial intelligence is a new concept, which is composed of fast and accurate machine learning capability to approach investment prediction problems.

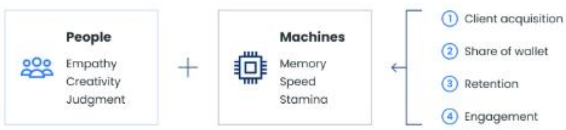

Fig 1: Wealth Management Solutions

1.1. Background And Significance With the rapid integration of finance and technology, financial technology (FinTech) shows an accelerated development trend in recent years. It involves technologies used in traditional financial service industries, such as banks and securities, including payment systems, trading platforms, intelligent algorithm trading, credit risk evaluation, and robo-advisors. Compared with traditional financial service providers, FinTech enterprises have advantages in both market and business models. They have a deep understanding and application of the Internet, using advanced technologies such as the Internet, big data, and artificial intelligence (AI) to better perceive market demand and user behavior patterns. Thus, they provide more convenient, faster, and personalized financial services and products.

As a comprehensively disruptive technology, AI is entering deep financial fields, such as investment and wealth management, through the integration of big data and high-performance computing. It is regarded as the core technology of the current technological revolution and industrial transformation and has received significant funding and attention from governments and companies worldwide. In the financial industry, AI is considered a crucial driving force for the development, upgrading, and transformation of the industry. AI-based FinTech products and services are rapidly emerging and have been infiltrating various consumer finance scenarios and industries. AI displays the ability of supernatural capacities in complex pattern recognition problems such as face recognition, political recognition, music generation, and voice generation, which is far beyond the human brain.

The capital market is an essential assembly mechanism for dispersed wealth, fund-raising, and risk aversion. It performs as the primary avenue for long-term asset preservation and appreciation. Currently, the wealth management industry is booming and seeing an explosive increase in clients, assets under management (AUM), and wealth management products (WMPs), especially in the personal finance sector in emerging economies. Financial investors and firms face highly complex, uncertain, and quickly changing capital markets and an overflow of real-time financial data. It is difficult for manually designed models and systematic exploration to untangle complicated market phenomena and correlations and to allow prevailing market models to be adaptive and applicable under a changing market condition.

Inspired by advancements in AI and its potential in the financial domain, financial intelligence, a new concept, is proposed to provide intelligent wealth management solutions for a smart capital market. Financial intelligence involves a data-driven and academic finance-aware approach to integrating AI and big data for financial-market modeling and prediction, trading, and wealth management. Its key insights are first interpreted, followed by recent advancements in various finance and investment strategies, disclosures of cutting-edge AI-powered wealth management systems, and an outlook for future father development.

Equ : 1 Intelligent Portfolio Optimization

$$\max_{\vec{w}} \left[\vec{w}^\top \hat{\mu}_{\mathrm{AI}} - \lambda \vec{w}^\top \Sigma_{\mathrm{BigData}} \vec{w} \right]$$

Where:

- $\vec{w}$: Portfolio weights
- $\hat{\mu}_{\mathrm{AI}}$: Expected returns predicted by AI models (e.g., LSTM, XGBoost)
- $\Sigma_{\mathrm{BigData}}$: Covariance matrix estimated using cloud-scale big data analytics
- λ: Risk-aversion coefficient

2. Overview of Wealth Management

With the rapid growth of the economy, wealth is produced at an unprecedented rate. The focus of the investment community has shifted from the efficient allocation of financial capital to wealth management, a rapidly developing industry that is relatively young compared to financial markets and investment products. This spurred researchers, practitioners, and investment companies from diverse domains to form various wealth management systems. While most existing research efforts may have contributed to formulating wealth management systems from different aspects, they have either focused on narrow areas or been heavily dispersed across diverse domains. In addition, many existing studies disregard the structure of wealth management and overlook important functionalities that have been less touched upon by the existing research, making it elusive for researchers from an overall perspective. Thus, a scientific characterization of wealth management using suitable standards and a comprehensive review of prior wealth management systems and issues is deemed necessary.

Wealth management, serving as an important part of asset management, is a service-oriented financial management service for the realization of high and stable investment income via the diversified allocation of investments. It aims at assisting individuals or families in acquiring, investing, maintaining, and passing on wealth. A wealth management system involves a set of functions that transforms raw user data into a product of wealth management services to that user where each function is realized as one or more well-designed algorithms. Wealth management is a relatively young industry in finance compared with financial markets and investment products. The faster the economy grows, the faster wealth is produced since the last 30 years in most developing countries. This shift in resource focus makes the allocation of financial capital to companies no longer the center of attention, which is also an important piece of concern for the regulators.

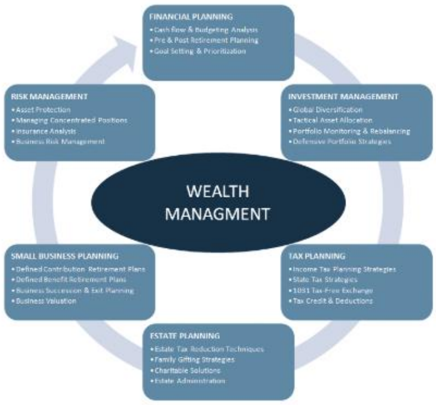

Fig 2:Roles and Activities of a Wealth Manager

3. The Role of AI in Financial Services

1 Introduction In the 21st century, diversified and luxurious lifestyles have emerged alongside rapid economic developments worldwide. The trend of wealth polarization is evident across the globe, and the demand for wealth management services has grown remarkably. However, high-end wealth-management services still require higher amounts of financial assets and management fees. Research and development has been shifted from financial technology (FinTech) performing trading/brokerage activities via application programming interfaces (APIs), to financial intelligence (FinBrain), in which AI technology integrates with behavioral science to replicate human intelligence and provide diversified interactive experiences. The need to provide small- and medium-sized individuals with wealth-management services has emerged. Robo-Advisor and financial product recommendation techniques maintain customer experience while mitigating financial risks. The traditional approach of wealth managers relies on simple rule-based analysts to screen stocks; this can only provide a general understanding of stocks, and cannot effectively characterize an individual’s stock preference.

2 Financial Services Banks and other financial institutions (FIs) such as brokerages serve as intermediaries between entities with deficits of funds and those with surpluses. The service areas between banks and other FIs are heterogeneous, with each type of financial intermediary specializing in a specific financial service. Traditionally, most banks focused on storing deposits and granting loans, while brokerages concentrated on underwriting corporate stocks and bonds as well as trading equities. By integrating AI-based technology into their operations, FIs can provide services to customers originating from other financial sectors. AI technology combined with big data can improve the efficiency of fund allocation and financial risk management. In the financial domain, banks and brokerages mainly deal with individuals or corporations either to meet their demand or to operate in a capital market. The demand from individuals mainly comes from high net worth persons from wealthy families and small- and medium-sized individuals from middle-class families.

Equ : 2 Real-Time Wealth Insights Engine

$$\text{Insight}_t = \mathbb{E}\left[\Delta\text{Wealth}_{t+1} \mid \text{AI}_{\text{Cloud}}(\text{Data}_t)\right]$$

Where:

- Insight_t: Predictive insight at time t
- $\Delta\text{Wealth}_{t+1}$: Predicted change in net wealth
- AI_{Cloud}: AI models hosted and updated on cloud platforms
- Data_t: Multisource financial and behavioral data

4. Big Data in Wealth Management

Between 2016 and 2020, the fast-expanding fintech industry underwent significant upheaval and widespread change, propelled by COVID-19, new digital technologies, and changing client needs. Fintech companies are now among the most well-known and cutting-edge organisations on the planet as a result of this rapid transformation. Their emergence has sparked the emergence of intense competition in the financial services market, forcing financial institutions that have steered a conservative course for decades to hasten their digital readjustments. A key enhancer of the wealth management sector is big data technology. Wealth management companies that adopt big data technology throughout the process will be able to accurately assess users' financial status. The wealth management industry was negatively impacted by the epidemic at first, but it quickly rose as the stock market rebounded. The arrival of economic transition brought fresh difficulties and fast evolving new demands. Investment portfolios, product restructuring, and brand reinvention all prompted a surge of businesses looking for analytical insights. Saxo Bank predicted that by 2025, funds and securities will increase from $346 trillion now to roughly $486 trillion. Concise big data is a fashionable catchword of the 21st century and is regarded as vital capital support for economic and social growth, similar to the notion of production factors such as land, labour, and capital in economics. The Oracle database giant introduced a proprietary term "big data" in 2000 to describe the capacity of traditional database technology to collect and analyze vast amounts of data. With the rapid growth of the Internet, mobile Internet, and Internet of Things technology, data has become a basic production factor and has the potential to provide new infrastructure for the wealth management industry. The Clarkson Pyramid discusses the principle of pyramid data. It is challenging to present, calculate, disseminate, and explain pyramid data due to big data lag. It is contended that big data technology can analyze users' non-linear cognition and portfolio behaviour with analytical conclusions that were previously impossible to detect in smaller data scenarios. Such knowledge will become a new source of motivation for modernization, competitiveness, and profit growth.

Fig 3: Big Data in Wealth Management

5. Cloud Computing: A Game Changer

Cloud computing is a transformative model that allows for on-demand and scalable access to a shared pool of configurable computing resources. This democratization of computing resources has led to a shift in computing paradigms, enabling individuals and organizations access to once taxingly costly services such as data storage and processing on a pay-per-use basis. Moreover, it allows for conveniently accessing large-scale systems over the internet wirelessly. For the financial industry, caution must be applied because financial institutions have sensitive data that can harm clients if mishandled. As it stands, banks and financial investment firms are still heavily reliant on legacy systems, which cannot satisfy growing market needs such as high-performance computing and big data processing, warranting the urgent transition to the cloud model. More goes on behind the scenes in the trading world than a handful of large financial institutions offer to mislead the remainder of the population into thinking the system is fair. In actuality, execution speed invariably wins clients, which motivated firms to invest billions into infrastructure that minimized latency. Over time, however, the latency advantages of speed became financially harder to come by. As a short-term solution, firms began to move from designing self-contained systems comprising the trading, order routing, execution and settlement process in-house to outsourcing all but the bare minimum necessary to gain (and keep) a client.

This risk is considered a melting iceberg: in-principle foreseeable but in-practice very hard to manage. To better monitor the risk, building a synthetic estimator of the usage of the service provider, possibly complemented by real-time scrutiny of API requests, alerting the client when something unexpected occurs, is the way to go. The running time is of the order of a few seconds because by definition the cloud industry relies on hundreds of microservices that offer small services over simple and standardized APIs, which leads to a high number of requests per traded product, in the range of 10s or 100s per second, hence orders of magnitude larger than the current risk model based on the drift of the prices on which triggering events are assessed. This method is also expandable to account for additional pieces of information, such as the estimation of the remaining amount for usage-based pricing, or more aggregate metrics that rely on the analysis of longer time periods regarding performance monitoring.

Equ : 3 Predictive Asset Allocation using Reinforcement Learning

$$\pi^*(s) = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \mid s_0 = s, \pi\right]$$

Where:

- $\pi^*(s)$: Optimal policy for asset allocation in state s
- $R(s_t, a_t)$: Reward function (e.g., return vs. risk tradeoff)
- γ: Discount factor
- Learned via RL agent trained on big financial datasets streamed via the cloud

6. Integrating AI and Big Data

From the clients' perspective, the provision of a Cloud-Powered Intelligent Investment Consultant is to provide them with emotional and psychological accord. The knowledge system can avoid some emotional and psychological fumbles. On the one hand, it can control fear and greed. On the other hand, it can give personalized reminders. From the wealth management institution's perspective, it is also an on-line prototype system for testing the provision of investment consulting services. The test results will provide quantitative inputs on the recollection of the knowledge system, the NLP technology used, and the proper implementation of information policies.

Hence, the aims of such a prototype system are to act as a wealth management institution's investment consultant to interact with clients by text and speech but without the need for a large investment consulting team. Quantifiable tests on the performance of the knowledge system, the provision of the investment consulting service, and the integration of NLP and speech recognition technologies can be automated. This prototype is a self-feedback and self-learning plug-in templated based emotional and psychological Intelligent Investment Consultant which leads despite text-based chat to spoken dialog systems. Considering the Cloud-Powered Intelligent Investment Consultant provision of wealth management services on a cloud computing basis, the scope of the system can be extended to media, AI chips, and virtual reality.

The provision of a knowledge base is indispensable for a cloud-intelligent financial consulting system. A knowledge base can be constructed from an existing database by combining expert knowledge, media resources, and professional experience. The knowledge can be stored by an enriched content-based representation K(N)` (X,(KI;DI)); where knowledge K, with meta knowledge M, guidance G, and situation S; N{(T,D)} for text data and (T,D),(F,D) or (T,D) for data in other media; content-based representation for interpretation R(N) and for retrieval T(N).

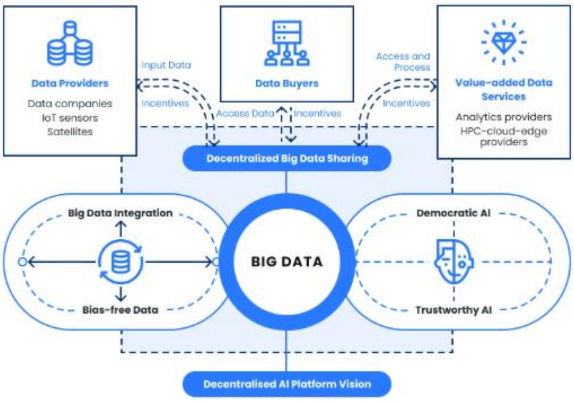

Fig 4: Integrating AI and Big Data

6.1. Data Collection Techniques Data is one of the core components behind making a wealth management solution intelligent. Huge amounts of data, such as macro-economic data, financial statements, and social media data, are collected, cleaned, aligned and processed. Compared with development data in common applications, finance data poses additional problems for researchers, with an emphasis on its unique characteristics.

It is constantly generated in high frequency but low volume. Even assets of the same type, such as stocks, exchange rates, bonds, and indices, may be released in different frequencies, creating datasets that suffer from irregular time gaps. The internet allows a new type of data to be produced in huge volumes, yet their quality is hard to maintain. Furthermore, financial data is highly dynamic and noisy, making it more challenging to deal with.

The great volume, variety, and velocity of data call for more powerful infrastructures to preprocess the data into a usable form. The pre-processing is often non-trivial, involving sophisticated data parsing techniques, database builders, and deep learning architectures. Depending on the types of data and financial applications, the deployment of the pre-processing efforts can vary. In general, graph data appears to have missed its pre-processing efforts in wealth management tasks, yet there exist widespread applications.

Complaint websites, news headlines and comments about financial events are often crawled anew with each hardware or firm's change, yet some firm- or hardware-specific data need to be maintained. Financial statements, historical capital structures, and trading data could be extracted from public exchanges or commercial vendors, and though they require a great amount of effort to clean and align, they need less maintenance after the establishment. Other popular data for enhancing wealth management solutions are also researched, but the commodification is yet to be realized.

6.2. Data Analysis Methods Portfolio optimization is an important area of research for financial analysts. Investors are looking for better portfolios that would maximize investments and returns while minimizing risk. Portfolio Optimization Problem (POP) is again a multi-dimensional optimization problem. In this work, a framework is proposed which will take into account both the quantitative and qualitative data sources available. A set of stocks is filtered for the analysis. The filtering of stocks is done by downloading the stocks from APIs. A few stocks are selected as results of pre-filtering. Then the mechanism for populating the stocks to the universe of the stocks takes place. The filtering of stocks is done from various sources of text which represent user sentiment towards the texts. The sentiment is classified into either positive or negative using a strong sentiment analysis technique. The stocks that received a lot of attention and gathered a large number of news articles are filtered.

The stocks that were aggregated a lot of interest were checked for significance using the Monte Carlo method simulation. Sentiment analysis of the news articles of several stocks was performed. These stocks, along with a few more stocks that had received a small amount of attention were then analyzed for their performance. An optimized portfolio is given as a result, that provides better results and risk diversification like the minimum variance stock approach. Portfolio optimization is one of the important areas of research among finance enthusiasts. Post liberalization in 1991, the Indian stock markets were opened up to the Foreign Institutional Investors (FIIs) which made it one of the fastest-growing economies in the world. The BSE Sensex today is regarded as one of the most competitive indices in the world.

With the advent of various information and communication tools, a huge corpus of data is generated every day. The trade of stocks takes place based on the information available and made public. The stock markets are also considered as efficient markets won by New York City due to a number of information sources available. However, the popularity of social media has opened up a wider spectrum of data sources that would give more (and sometimes even better) information compared to the traditional news articles. The Twitter feeds containing patterns of news posted and the comments and feedback received play a key role in sentiment analysis. Sentiment analysis of a document assesses the polarity of the text, whether it is neutral-to-positive or neutral-to-negative.

7. Benefits of Cloud-Powered Solutions

Emerging financial technologies can create a more efficient, transparent, and user-friendly wealth management ecosystem. However, they require an overhaul of traditional models. The financial management landscape is increasingly moving to the cloud. As such, incumbents must rethink their value propositions and cooperate with potential challenges to find a cloud-powered balance. Financial institutions must ensure a balance between customer needs, regulatory compliance, and product nascence while managing data sources required for accurate forecasts, as well as the large amounts of historical data accumulated along with data privacy. Wealth management firms will require technological support to meet these demands, which presents an opportunity for emerging fintech firms.

Acknowledging the opportunity, the team proposes an on-demand solution to embed machine learning for real-time forecasting combined with cloud computing efficiency and integration capabilities. The proposed solution will also predict the utilization of various financial products and enhance transparency with an integrated data management and sensor visualization environment. Adopting such a holistic solution will streamline the collaborative establishment and ongoing product development with new, innovative financial actors, enabling keeping pace with development for mass-market access in 2-3 years. Such a decision entails an evolution of the existing business model in wealth management and requires a trusted partner ready to support changing business processes.

A plethora of services and solutions will be enabled through data and resource integration on a comprehensive business cloud. For users, solutions range from modular, integratable, do-it-yourself financial management applications to a digital but more personalized but passive foresight financial adviser. An added value of the cloud service ecosystem is the provision of opportunity-based and holistic financial insights to multitude stakeholders through simulation, exploration, monitoring, and prediction services realized through interoperable data, models, and smart contract applications.

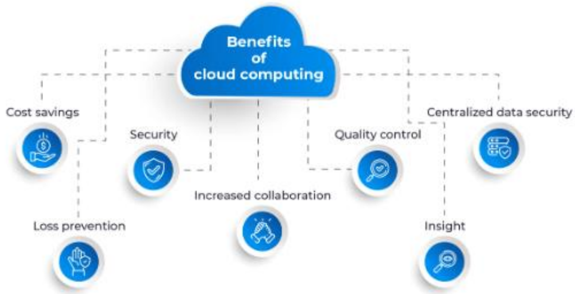

Fig 5: Benefits Of Cloud Computing

7.1. Cost Efficiency Cloud-powered financial intelligence is an emerging technology that offers innovative wealth management solutions for asset management clients' everyday demands. The wealth management industry is customer-oriented, and understanding consumer needs is a determinant of success. Large financial institutions strive to provide all services under the same roof. In addition, personal assistants help wealthy clients decide on investments, portfolio allocations, and risk management. Cloud-powered financial intelligence implements machine vision, natural language processing, speech recognition, and big data analytics technologies. The models and required data are stored in the cloud to provide high-performance computing on a pay-as-you-go basis.

A cloud-powered financial intelligence application detects the portfolio of documents from a market surveillance report, finds those documents, and sends out extraction requests. After completing the requests, native documents, extracted documents, and standard documents are sent back to the client through a web-based application in a unified format. Clients can send messages back to the service provider to inquire more details about some extraction records via the web application. The automated hybrid system reduces the manual work from more than two hours to three minutes, preventing excessive humanitarian costs. It is formally tested and well-accepted by clients. Another cloud-powered financial intelligence application estimates firm performance metrics from earnings call transcripts. It evaluates performance metrics around the earnings announcement date and generates performance evaluations against officials, analysts, and investors. Adoption of cloud-powered financial intelligence in the capital market is still very limited. It is an excellent opportunity for future research with numerous data applications.

Technological advancement has transformed the financial measurement landscape of share price prediction, fundamentally improving the modelling process. Large unstructured textual information and datasets have become available alongside significant growth in computing facilities. Traditional financial measurements based on static impact factors presented a limited understanding of share prices. In contrast, the continuous-processing techno-financial social analytics provides an alternative study of share price prediction. Share prices are influenced by cash flow expectations and changes in risk perception around earnings announcements. Textual information from earnings call transcripts affects prices and propagation patterns in markets.

7.2. Scalability

To remain competitive, wealth management firms need to access and understand relevant data faster than ever before. A traditional wealth management firm gathers information through a team of dedicated research analysts, who comb through research from many different sources and distill their insights into high-quality briefing notes. Collecting, aggregating, and distributing this information is a labor-intensive process. The introduction of AI-powered research tools can help surf the infobesity wave with comparatively little effort, and wolves of Wall Street-style deals will become much rarer. Going beyond distributing information to understanding it will require sophisticated big data analytics. This analytical intelligence, wherein data is aggregated into insights for actionable use, cannot be retained in spreadsheets or relational databases. Unrealistically high levels of compute power will be needed for the processing, which far exceeds the capabilities of a single workstation. This constraint led wealth management firms to mass hack “black box” solutions from cloud service providers but to little avail. Recently, the financial industry has sought to hire tons of data scientists and engineers, building an endless snowball of problems instead of real products.

Wealth management AI cannot be implemented in strategic stasis. Just as companies began using spreadsheets for rapid growth, they will need to create a software layer integrated with an underlying resilience and adaptability to deal with an ever-increasing wave of data. As the first iteration failed even with heavy investment, the new paradigm focuses on aggregating existing modular building blocks and building them on top of elasticity. Cloud-based solutions already come with this flexibility and speed, while the extracted insights will drive the business. Money spent on usage-based pricing will not become a sunk cost when companies inevitably need greater power. On the contrary, any IT investment made now will wilt slowly due to underutilization.

Rapid granularity and searchability of relevant information can open new ways to cross-collateralize funds into mega-M&A transactions. With deeper natural language processing and sentiment analysis, a more intricate understanding of operator rationale can be derived. With bigger datasets and domain knowledge of macro/industry correlations, a proactive early warning system can be designed. Solutions for all aspects exist, it is not hard to put together an impressive deck. It is just that everything would be very subtle and difficult to onboard for non-tech-savvy business personnel.

7.3. Accessibility As clients increasingly seek out technology options in wealth management, more financial institutions are forced to look to technology for competitive advantage. As wealth management customer segments diversify with more millennials and Gen Z clients, firms must seek to provide more integrated and accessible investment management through technology while scaling offerings for high-net-worth clients. Legacy vendors offer several features and systems for wealth management and investment management separately, while newer vendors provide only basic features for each. A solution that incorporates comprehensive, native infrastructure powered by cloud technology will benefit all firms. Architecture would start with individually managed accounts (IMAs) supported by unique tax optimization, customization for goal-based investing, and risk management. A mobile display would allow clients to view information about their accounts and communicate directly with managers. Both would be accompanied by cloud integrations that allow direct data transfers with custodians and pricing vendors, ensuring fewer interrupted trades, more accurate accounts, and improved overall experience. The data assembly, navigation, and processing would enable strategy backtesting, monitoring, and performance attribution. As the client segment in the wealth management industry shifts towards the younger generation, firms behind the curve need to adopt technology promptly before it becomes obsolete. After the core architecture is established, add-on features enhance the service through further integration across the investment management and wealth management stacks, aiding with compliance, risk management, and lowering labor costs with AI-driven tools or increased access through automated managed accounts at a lower AUM target. The first step of architecture development relates to IMAs, a cousin to mutual funds with individualized portfolios. These are fit for firms with an established customer base that previously only offered white-label funds to clients approach because of the added complexity to invest, especially in tax-inefficient accounts, together with recent shifts in investment expectations necessitating individualized funds. IMAs must be supported by tax optimization, customization for goal-based investing, and direct management of risks.

8. Challenges in Implementation

Investment management is one of the sectors where machine learning can bring significant added value. However, not all considerations are straightforward. Fund management companies still face significant barriers to implementation. 38% of senior level managers report a lack of required infrastructure for implementation. This number rises to 41% at C-Level roles. The second most cited most important barrier to implementation is siloed data and siloed organizations. Wealth companies should start utilizing cloud computing to get the most out of their machine learning algorithms. Some investment management companies have not digitized all aspects of their business. Steps need to be made to achieve this techficient state. Investing properly in IT infrastructure is needed to get to use artificial intelligence. AI systems depend on large amounts of data. Therefore, data quality is crucial when using algorithms to solve specific problems. Regarding the dataset used for training, it can be biased. This should be considered when using AI and machine learning in asset management companies. Supervised learning algorithms such as regressional approaches and neural networks may provide answers for management questions. However, an additional risk arises when the quality of data is not recognized. The data on which the questions are solved comes from various sources and either has a varying data collection period, a different method of collection, or data could be missing. This is true also for the collected data regarding investment styles.

A risk occurs if the bias in the data is neglected. In this case, the tests of results may have the same bias. The influence of this bias can be prevented by using transparent models and/or by investigating the model's attributes for which dimensions are being taken into account for predicting the next value. The latter is important to keep fairness and avoid implicit bias in the predictions. A common problem with AI is concerned with the ability to explain results from predictive models. A lot of AI models are such that they can either not be interpreted at all or are very complex and provide results in black boxes. In central banks, predictive models used for decision-making need to be explainable. This is because consequences of decisions are interpreted by the model; therefore, insights into what drives these changes is needed to be able to deal with them through policy implementation. In the community of asset management companies, transparency also plays a crucial role. A key requirement of investment decisions is the ability to explain why an investment is made.

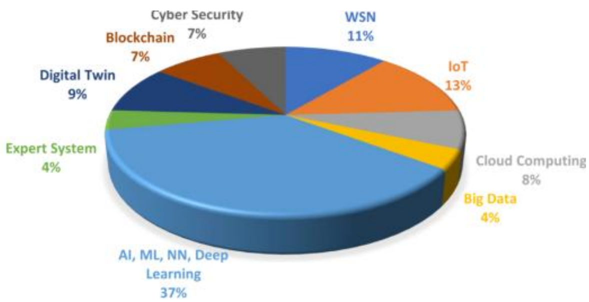

Fig 6: Cloud-Powered Financial Intelligence

8.1. Data Security Concerns The continued evolution of the Smart-everything movement and facilities powered by Artificial Intelligence (AI) have given rise to innovative technologies and services in the FinTech sector, alongside sophisticated cyber threats previously only theoretical, and which were previously countered by traditional detection methods. The emergence of new technologies comes with new opportunities but also poses critical security threats. FinTech emphasizes great technological innovations aimed at automating financial services to save costs and time for customers, which draw the sector into a vicious cycle of enhancing its defensive security strategies to counter emerging threats while trying to minimize costs and maximize productivity. Furthermore, digital threats targeting organizations are regarded as one of the most significant threats in any industry, and the rise of financial technologies marks the rise of digital threats towards FinTech. Threats target the information and data of organizations and businesses that are widely considered the most precious asset any agency can have.

Technological evolution arms not only legitimate sectors with sophistication, actions, and tools but also grants malevolent actors enhanced tactics and cumulative knowledge in executing advanced cyber-attacks. The structural push towards e-business and online e-commerce, and the widespread adoption of the Smart-everything movement and cloud facilities by many Financial Organization Institutions (FOIs), have been accompanied by a dramatic increase in cyber threats targeting the financial sector. Coinciding with this research, the finance and insurance sector ranks among the industries in which cyber criminals have made their most attempted targeted attacks. The rise of FinTech, alongside the threats targeting FOIs, raises essential questions regarding the understanding of forthcoming digital threats, especially pricing adaptation and investment in countermeasures to tackle that digital assault. This study attempts to furnish findings and insights for FinTech stakeholders and financial servers intending to comprehend the present state of data-centric threats and defenses in FinTech.

8.2. Regulatory Compliance Governments and regulators are increasingly creating new laws and imposing fines on businesses that mishandled personal data. This has huge implications for financial firms. Today, financial trading and investment management teams require an ever-growing amount of data and computational power, and AI is a way to gain an edge over others. Nevertheless, there are huge challenges involved, including fast-evolving source types and formats, integrated storage across asset classes, stringent regulatory and compliance monitoring, cloud-based infrastructure, and more. Model selection, customization, and training, alongside risk and compliance monitoring, should also be considered. The proposed cloud-powered financial intelligence fully manages the lifecycle of data, computation, and models for wide-scope asset allocation and portfolio management. It is composed of the data and infrastructure provisioning service, data and computation access control service, risk monitoring service, and compliance monitoring service.

Governments and regulators around the world are enacting new legislation and imposing fines on companies that fail to adequately safeguard personal data. This realization has major ramifications for financial firms, global leaders in personal data handling and analysis. They strive to develop new services, including digital wealth management and management of private data for asset trading, while they must treat the data sent from users in accordance with privacy regulations, surveillance policies, and compliance requirements. Digital wealth management utilizes AI to design investment portfolios tailored to clients' profiles, budget, and risk tolerances. Emerging start-ups provide low-cost financial advisory services based on clients' information analyzed by machine learning algorithms. Machine learning is also widely used to pre-screen non-public information on stocks, following the logic behind insider trading. From a surveillance and compliance requirement point of view, the data will be scrutinized closely by AI-based monitoring systems. At the source level, all communication messages about the stock should be extracted, translated and understood, and the rationale or intention behind the decision to act on the stock should be inferred. At the motivation or output level, the trading behavior should be monitored to ensure that the heuristic behind the decision or coding logic has complied with the regulation, and trades founded on non-public information should be flagged.

The proposed vision is a comprehensive financial intelligence system powered by cloud engineering and AI techniques. It fully manages the lifecycle of data, computation, and models for wide-scope digital wealth management and surveillance. It interlinks the data provisioning and infrastructure provisioning on various data sources, designs production-grade architecture and detailed components for dynamic user-adaptive cloud provisioning, implements adaptive industrial strength wireless communication networks for data ingestion, and automated AI training, model design, implementation algorithms, and continuous in-production monitoring and transparency auditing.

8.3. Integration with Legacy Systems

As clients age, complicated issues emerge in terms of legacy systems. Some systems leverage a proprietary backend that was built over two decades ago, with most features written in C++. Many other organizations use AWS for regulatory archives and handle advisor data verification on a spreadsheet that is updated once a week. Both strategies have issues with data collection and duplication, redundancy and reliance on back-end administrators who conduct semi-manual operations on spreadsheets. However, some of the banks built their financial servicing systems by collecting their IT components through acquisitions; thus, they have become fractions without any common data formats or a single point of integrity. In some areas, data is duplicated across dozens of SQLs and backend systems. Regulatory compliance regarding data protection to prevent leaks, data victimization, double spending, and alert problems on behavioral data, would remain at the very heart of this matter. With respect to the third-party Integrators framework, it means middleware, business process management (BPM) and ETL. Then the transformation engine channels signals, generates logical markets that respond in real time to the security market tickers, and executes intelligent order execution algorithms. Price war, latency arbitrage and overall trading infrastructure are addressed through a formidable marketplace where orders can match according to a market automaton entity with reliability and anti kickback measures, thereby perfectly addressing “risky” signal exposures. The regulatory compliance engines are available for instant integration. Direct payment processing through up to 30 processors is also possible, meaning every financial service a wealth manager may render is addressed.

9. Conclusion

The cloud is driving a change in the way wealth managers provide services, such as forecasting and asset allocation. Cloud computing allows firms to concentrate on their core competencies and outsource more standard tasks. The capital cost of hardware and software is much higher than the operating cost. The continuous development of AI technology is leading to significant progress in big data analytics. Customers demand the analysis of potential profitable trades in real-time, which can lead to big trading. Intelligent and automated trading procedures allow firms to bypass human processes, speed up execution, and enhance price efficiency. It is modern firms' overall competitive strategy to combine huge data and advanced technological means.

Modern wealth management firms usually use macroeconomic variables to explain and estimate market variations, which can be time-consuming and often ineffective. The academic community endeavors to capture the non-linear dependencies among the input of huge historical trading data, to reproduce the behavior of the market at its closing time. Actually, the markets are driven by investors and their actions toward their interpretations of available information. A deep understanding of the feedback information on the response time scales of funds is the key to fleeting trends' identification. Leading indicators, things that transform data to gain insight, can result in trading advantages. Recent developments in information technologies allow virtually all market data to be collected and communicated in digital format. Financial data science has emerged as an interdisciplinary branch of science, which applies the techniques of big data analytics to the financial domain.

A wealth simulation approach for better performance on both asset allocation and stock selection objectives is proposed. Two centralized wealth focusing on a few activities and lots of supplementary information with fuzzy well-defined securities are incorporated into the multi-activity processing simulator framework. The simulation processes have a time complexity of O (n + m) and are implemented parallelly by default. The method generates one alpha and suits the context. If a context is missing, the matching matches are dispersedly integrated. By the branch-and-bound pruning method, the simulation depth can be contributed to rules.

9.1. Future Trends

The credibility of conventional wealth-management processes providing them with an edge over automated and virtual services is important. Nevertheless, there are opportunities for improvement for conventional wealth-management processes because of the sophisticated algorithms of AI service providers. The degree of ownership of customized and personal robot-advisors is built on the capacity of the latter to dominate the fundamental thesis of financial systems used, access to knowledge of the assets and to manage their risks. Besides that, there are values that conventional models could infringe or conflict engagement patterns, i.e. in terms of ethics, regulatory discordance and moral obligations. In short, mechanism-driven recommendation systems need to be scrutinized and evaluated carefully. As an example of a rapidly evolving domain, Robo-advisor business is examined. AI-powered wealth-management services are analyzed, identifying the salient areas of operation and engagement different a wealth-manager might have with his clientele. Firms in this context are further classified in terms of delegated or assisted service in combination with pre-defined or customized recommendations. Robo-advisors' potential ability of lowering the average risk of an investment portfolio is also scrutinized as one of robot-advisor services. In many recent works, it has been shown that most portfolios in usage are not optimal in terms of return/risk ratio pointing out the potential inefficiency of AI-powered Robo-advisors when calculations are based on information stemming directly from investment banks and retail brokerage companies. Optimal investment decisions can be made based equally on empirical time-series data points or fundamental knowledge on sectors or firms. Regarding the research methodology on the immense data collection, supervised and unsupervised machine learning algorithms can be utilized. The accurate supervision is not always guaranteed. These inferences could yield spurious correlations that prohibited classical models to implement in wealth-management processes because of theoretical rigidity and mathematically extreme approximations.

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