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Research Article

Revolutionizing Wealth Management: The Role Of AI, Machine Learning, And Big Data In Personalized Financial Services

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ABSTRACT

Financial institutions invest enormous amounts of money and other resources in many areas. One of the big development areas is wealth management, outsourcing the investment advisory services of employed investment professionals to software solutions based on artificial intelligence technology. Driven by technology, fintech startups have emerged to challenge the traditional industry, creating disruptive innovations that have attracted many new customers and hundreds of millions of investments. This paper provides an overview of a FinTech phenomenon when so-called Robo-advisors revolutionize wealth management. The objective is to introduce Robo-advisors as a low-cost, scalable, unbiased, and convenient method of automated investment recommendations and wealth management. The focus is on the investment advisory services of wealth managers and global trends influencing wealth management.

The financial services industry is one of the first, most heavily regulated, and examined industries. The universal banks of the large systemic institutions have dominated financial services with their personal, local knowledge, and tailored services to affluent private customers. Because of the high profitability of the wealth management business, resistance toward large cracks, such as those suffered in investment banking and assets management, has remained firm. However, the last decade-long before the recent massive global market offensive held up by FinTech incorporated experiments at their own financial well-being in addition to traditional money sources. Numbers of HNWIs increased significantly globally. FinTech companies have used a broader definition of the term and included forex and CFD traders in those providing wealth management services as well. FinTech has revolutionized robust and cheaper money transfer mechanisms with various solutions for retail clients. On the other hand, Robo-advisors as a novel and technologically advanced investment service alternative have gained popularity among retail clients in that most populous and wealthy part of the population. The discussion on the definition of Robo-advisors and their set-up focuses on the black-box transparency dilemma.

Keywords: AI, machine learning, big data, wealth management, consulting service, automatic portfolio selection, big data analysis.

1. Introduction

This paper focuses on the role of Artificial Intelligence (AI), Machine Learning (ML), and Big Data in wealth management as a response to the increasing competition in the financial industry in the digital age. Investment advisory service, an essential service in wealth management, has aroused growing interest among practitioners and academics. Effective investment advice has a significant impact on the growth and stability of the market and is tightly linked to the overall economy. Some clients' portfolio investment behaviors are analyzed through sophisticated algorithm-based quantitative models, while others' behaviors and decisions are predicted through sentiment transmission analysis based on Natural Language Processing (NLP).

Wealth management entails providing clients with investment advisory services, formulating an asset allocation strategy that matches clients' risk appetite and investment horizon, selecting suitable investment instruments, and applying the determined strategy to the financial markets. Based on the level of interaction with clients, wealth management services are categorized into four types: private banking for high-net-worth individuals, traditional wealth management for mass affluent clients, online wealth management for mass-consumers, and Robo-Advisors for retail individual investors. Robo-Advisors, a type of AI-based investment advisor, provides fully digital, automated, low-cost wealth management services with universal access at any time and anywhere.

AI technology combined with Big Data enables industry players to deliver more accurate products and services to customers efficiently. The technology can mitigate information asymmetry to improve fund allocation efficiency, detect and control the risk management process, and reduce the risk of investment loss. Personal identification recognition communication, recommendation, and data analysis are effective means of enhancing engagement and customer experience in finance. By employing traditional and new technologies, Roboadvisors build the capability of automating the tasks of human advisers by a multi-circle and automatic-financial-advisory process, which consists of customer onboarding, account checkup, portfolio building, and monitoring.

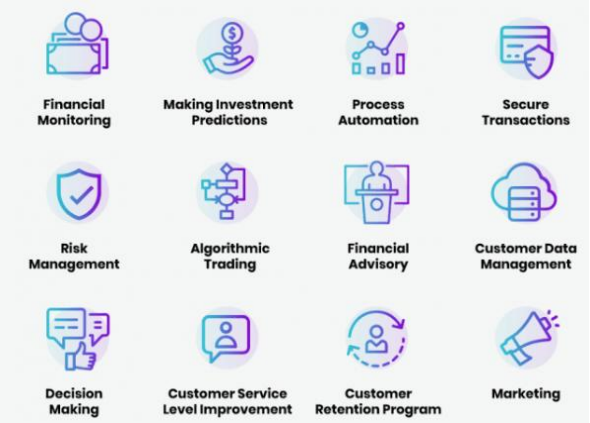

Fig 1: Machine Learning in Finance

1.1. Background And Significance

As a result of the digital revolution that is continuously shaping today's business environment, many companies are becoming entirely digitalized and technology-based. The banking sector is no exception, with increasing digitisation amongst retail and corporate customers. The development of technology within this area has many effects; furthermore, the changes in human consumption and behavior bring challenges and opportunities for financial sector players. The investment management industry is going through a fundamental change driven by major market forces. Investment executives recognize the need to adapt their business models. Disruption from automated investment advice, coupled with the arrival of many new market entrants, is forcing existing players to quickly build a digital customer interface. Customers are also becoming more digitally savvy and increasing the use of online banking and trading services. These developments have resulted in intensified competition. It has also led the existing players to reshape their infrastructure in order to enable cost efficient and scalable operation. The continuously developing technology has been able to revolutionise both the simplicity and complexity of tasks that humans perform today. In highly complicated fields of services, such as consulting, law and thus financial services, it has been argued that the true impact is not yet known. Investing in human capital has not only been necessary for the classical case of understanding but also for desire and intention for a long time. Technology does not only read a shareholders' letter or an analyst report; it can also decipher and understand the likes and dislikes of a targeted audience or a potential customer. Artificial intelligence offers many possibilities on how to revolutionise the wealth management industry. In a broader view of the industry, digitalisation and automation of tasks have noticed significant development. From the individual investor's perspective, increasing online services for trading, alternatives to self-directed investing with big brokers and banking systems have diminished the level of personal interaction. The latter have realised the importance and benefits of early integration in the easy-to-use Internet related tools to ensure retaining their customers. As a consequence, many large banks have developed or invested in various forms of investment and trading platforms.

Equ : 1 Portfolio Optimization with AI

$$\max_{\mathbf{w}} \left(\mathbf{w}^\top \mu - \lambda \mathbf{w}^\top \Sigma \mathbf{w} \right)$$

- $\mathbf{w}$: Asset weights
- μ: Vector of expected returns (learned via ML models)
- Σ: Covariance matrix of returns (from Big Data)
- λ: Risk aversion parameter

2. The Evolution of Wealth Management

Wealth management aims to ensure clients' prosperity and meet their financial needs, considering macroeconomic changes and personal economic situations. Traditional wealth managers provide diversified and risk-minimized investment advice based on the clients' financial standing, investment strategies, and risk tolerance. These services are inefficient and expensive as they require manual, rule-based, and expert-based setups. In addition, large and diverse wealth-management markets lead to information asymmetry. Innovative financial technologies help mitigate information asymmetry and human-based services. AI technology combined with big data can integrate long-tail markets and alleviate information asymmetry to help improve efficiency in fund allocation and financial risk management. Identity recognition and natural language processing technology allow machines to replace workers to provide interactive services to customers. When financial intelligence meets AI, it can provide ordinary people with inclusive financial services to meet their financial needs.

However, traditional professional financial services have a high threshold, and the financial needs of ordinary people are not well met. Thanks to credit assessment technology, the financial threshold can be significantly reduced, which helps provide better services. Recently, the need to provide wealth-management services for individuals has emerged. Robo-Advisor, financial product recommendation, and precision marketing can maintain a good customer experience while reducing risks and helping customers improve their decision-making capabilities. Based on various and abundant client-side factors, such as social and economic status, wealth managers can provide precious wealth-management services. However, most wealth managers only employ simple rule-based analytics based on reporting systems, which cannot effectively characterize clients' preferences and are cumbersome and expensive. Therefore, new wealth-management service technologies are needed.

On clients' sides, wealth-management service demand can be regarded as one type of fine-grained query. There also exist massive datasets of stock information, which decreases the expensive threshold of providing wealth-management services. Advanced financial technologies, such as user profiling, predictive analytics, Internet of Things (IoT) intelligence, and customized recommendations, can help improve wealth-management services. Firm-side wealth-management service provides personalized recommendations for individuals. By utilizing information from clients' IoT ecosystems, wealth managers are able to characterize the individuals' behaviors and preferences and make real-time recommendation of stock investment decisions and asset-allocation advice according to individuals' real-time economic situations and personal life experiences.

3. Understanding AI and Machine Learning

AI - Artificial Intelligence is a broader field. Machine Learning is a branch within the field of Artificial Intelligence.The term "machine learning" has various alternative definitions in general use. While a definition coined in the early 1990s by machine learning pioneer Tom Mitchell may still hold sway, it does not emphasize the distinction between systems that are merely programmed and those that learn these programs from the facts. Maybe a better definition would emphasize that the subject is concerned with systems that learn computer procedures from data, experience, etc., through some generalization process. AI is either weak or strong, depending on whether or not it is thought to be duplicating the full behavior of a human mind. Many researchers believe that weakest AI is already widely deployed in today's technology, and scientists, philosophers, and writers have expressed visions of the world by machines exhibiting strong AI, from heaven on earth to Armageddon.

On this wide description of the field, many areas can be identified. Great paths of research exist within AI, such as expert systems, neural networks, genetic algorithms, emotionality, agent architectures, robotics, etc. At the same time, AI coalesces with many sciences. The computer scientist subfields of machine learning and natural language processing are important in AI, as are the psychology subfields of cognitive science and cognitive development. Similarly, AI is a cornerstone discipline in philosophy, linguistics, computer and systems engineering, and mathematics. AI therefore touches upon the basic things people care about: mind, language, decision making/control, physics, money, etc. Subfields and theoretical approaches of AI can be grouped into aspects of belief-understanding, design-manipulation, and behavior-emotion. This corresponds to knowledge representation, other reasoning methods, and agent or robot technologies.

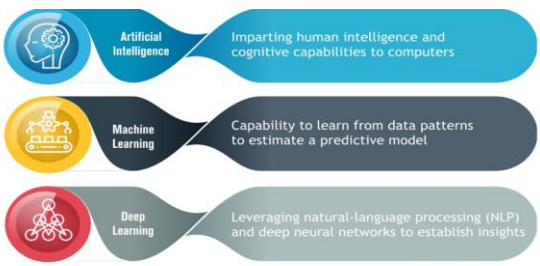

Fig 2: AI and Machine Learning

3.1. Defining AI and Machine Learning

Artificial Intelligence (AI) is disrupting a wide range of complicated fields of services, such as consulting, law, and financial services. The digital revolution is reshaping the traditional business environment of the banking, asset management, and insurance industries. The term FinTech (Financial Technology) has been coined beside information and communication technology (ICT), which refers to continuously developing technology. Technology-driven processes have already altered the ways of working and used to wonder about what robots can do and how they can replace humans, and improved efficiency of a firm. However, technology could be given an opportunity to be aware of the present understanding of finance and build cognitive intelligence from learning deliberately. Key trends emerging from current and social banking environments include peer-to-peer lending, crowdfunding, blockchain, and personal finance. AI impacts several fields where big amounts of data and high-level expertise is needed for decision-making. It is applied in credit decisions, risk management, fraud prevention, trading, and personalised banking in financial services.

Digital investment advice is an innovation of FinTech that has appeared recently and has received increasing attention. AI can revolutionise the wealth management industry. It is widely believed that hired representatives or advisors will be replaced by robots in private investment management. Autonomous investment can include automated asset management, automated stock trading, algorithm trading, and high-frequency trading. Utilisation of robots to provide advisory and management services in wealth management and investment advising is an emerging trend. Robo-advisory systems are digital financial advisory platforms that provide investment advice automated, algorithm-based, or both. They have gathered significant attention among financial services providers and suitable targets for many investments, concerning market size and expected returns. There are digital robo-advisors that have been established with traditional finance as a backup and there are competing companies within the FinTech industry with a pure technology approach. Nonetheless, their business models can differ widely. Robo-advisors can be divided with respect to investment philosophy, methods, and strategies. With the increasing use and understanding of AI and associated technology alternatives, financial service providers are forced to evaluate the implementation of AI in their investment advisory processes. The implementation must be evaluated thoroughly concerning advantages, disadvantages, and ethical questions.

Equ : 2 Personalized Investment Recommendation Score

$$R_i = \sigma\left(\sum_{j=1}^{n} \alpha_j f_j(x_i)\right)$$

- $f_j(x_i)$: ML-learned features for user i (e.g., age, risk tolerance, income)
- α_j: Weights learned from model training
- σ: Activation (e.g., sigmoid) to normalize score

3.2. Historical Development of AI in Finance

The first traces of artificial intelligence in finance go back to the 1980s when the. In the years following, some banks and broker firms were dedicated to mimicking human psychological needs and emotions. In the following decades, with technological advances, several financial institutions developed strong computer programs, and on some occasions, they treated them as their most sacred secrets. After a period of positive results, the unexpected market movement in 2008 led to some questions about the models' reliability, and mainly about the absence of control explanations on analytical models. As a consequence of this event, more measurements and conditions were established by governments and regulatory authorities on this type of modeling. After that, in the last decade, unsupervised learning methods showed rapid success in image classification and natural language processing. In the past decade, several financial entities started to use deep learning methodology to process unstructured data and make decisions based on the discovered features. The importance of these methods is that they recognize patterns in datasets without prior human screening and analysis of what could be meaningful. This evolution fell under the "big data" umbrella. This term comes from the need for new computational techniques to analyze very big datasets that were created by data mining and recorders. In . This precocious notion of financial use of AI is very wide and made clear that human perception of AI needs to evolve. In parallel, all significant actors in financial services are investing in "data scientists," mathematicians, and computer programmers capable of creating machine learning techniques. By this, financial data handling was raised to the levels of hard-natural and applied sciences. Distinct professional backgrounds gather together to treat financial data, algorithms, and analysis, based on statistical, financial, and economic foundations.

4. The Role of Big Data in Wealth Management

Big data has emerged as a game-changer not only in wealth management but also across various disciplines. The fashion industry can now forecast the taste and preferences of customers based on various factors including their shopping segment, geographical location, and psychological insight through data analytics. Music streaming apps have made recommendations for personalized playlists based on the listening history of the

users using machine learning models. Therefore, wealth managers or financial advisors need to think about their future in this world swamped with big data.
Past investment behavior is the prime determinant of future investment behavior. The wide presence of social media has provided an ample amount of input for firms that have noticed unprecedented behavioral changes in investors. Instant mass communication along with influences has made it highly volatile markets which are prone to irrational price swings. Wealth manager companies need to understand how to address investment decisions using big data on social media.
Wealth management companies and investment banks have direct access to the financial investment history of the customers along with their KYC details. Companies develop holistic analytical dashboards for their wealth management employees and investment advisors. These dashboards comprise thousands of historical product purchase records. Based on past investment behavior, they crawl the entire records of other similar investors, find products which those customers have added to their investment portfolios, find the number of number crunching features of those products, and finally suggest those recommendations tailored to the customer's preferences.
World-class wealth firms invest millions of dollars to showcase their fund families' performances to a huge audience. They hire professionals for direct marketing in the form of telemarketing, emails, etc. to target the customers. Wealth firms collect detailed data on these marketing responses including the investor's contact history. The analysis of this data with marketing investment helps in computing ROI from every marketing activity.

4.1. Defining Big Data

Big Data refers to data that is so big, fast, and complex that it is difficult or impossible to process using traditional methods. Big data comes from many sources. The variety of a big data set includes different types of data, such as structured and unstructured data from records and documents. For financial services firms to understand the changing needs of different market segments, they must use a wider range of data from different sources. High-volume data refers to the amount of data and databases generated every second that are challenged by either being too large or too difficult to process using traditional methods. Volume refers to the sheer amount of available data, where more is often better. As organizations consume larger volumes of data, they are able to provide better insights. The third characteristic of big data is high-velocity. Velocity refers to the fast-paced generation and transfer of big data. Data is continually being generated from a variety of sources at unprecedented rates, and organizations must be able to manage and capture this data as it streams in. Real-time behavior monitoring is essential for this, for example, capturing comments the moment they are posted.
Additionally, at the moment of creation, data must be ingested and processed in real time before it becomes worthless. In applications such as fraud detection, idle time means lost opportunity. The fourth characteristic of big data is high variety. Variety refers to a wide range of available data types, such as data from structured databases to unstructured text. Different applications are better suited to analyze or extract insights from different data types than others. Given the range of different data types available, it is essential that organizations are able to combine data from various sources into a single repository in order to maximize analytics potential. Hadoop-style databases are useful for this as they are able to store raw data.
The fifth characteristic of big data is a high degree of complexity. Complexity refers to the difficulty of using raw data to generate insights. There are two forms of complexity: 1) heterogeneity, which refers to the difficulty of integrating or joining different datasets from different systems; and 2) readability, which refers to the difficulty of accessing and generating human-understandable insights from raw data. For example, to simply find out how many of its clients are on Twitter, a finance company would have to run a highly complex and heavy process that rarely yields timely insights.

4.2. Sources of Big Data in Finance

In the financial industry, Big Data is available from a wide range of sources. The data can be characterised as follows: 48% is from social networks, 39% is from economic and financial news, 35% is based on structured market events and other sources include direct-marketing records, ratings, patents, company biodiversity records and also sensors, cameras or satellites. The availability of new forms of data improves predictive capability because more information on the relevant variables is provided and reduces the idiosyncratic noise in the data that can mask the underlying patterns. But as hard or soft, economic or non-economic data, Big Data is independently capable of improving predictions, especially in an international context where local banks are unable to exploit the data well. When shared with regulators, it can also yield a net gain for stability.
The financial industry is among the most information-intensive sectors, with huge amounts of raw data available. The operational capacity of financial firms seems to have kept up with the growth of data or to have adjusted to it. However, more important than the sheer quantities of data are the "new forms" of data that became available. Data is regarded as "new" only if some of the following characteristics are fulfilled: previously hard-to-obtain or near-unavailable information that was once deemed by the agent as irrelevant has become abundantly available; previously unstructured data has taken on a structured form; and finally, previously easily adjustable variables have de facto remained fixed over long periods of time. As for data in finance, the new forms can most easily be regarded with respect to these characteristics: 1. Social network data on opinions

regarding financial instruments/products, firms, markets and events; 2. Sentiment data based on news coverage of firms, financial matters or the relevant market; 3. Data on ratings and analysts' assessments regarding firms/products and also on their tracking of other agents; and 4.

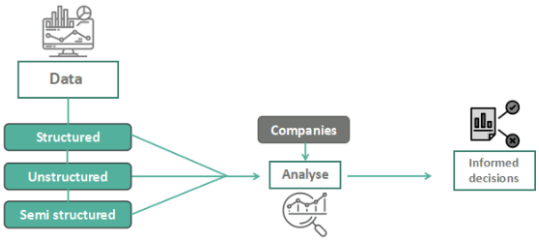

Fig 3: Big Data In Finance

5. Personalization in Financial Services

More than ever, the financial services industry has entered a new age of exploration. A wave of technological innovation has arisen as a result of years of infrastructure creating a data environment that is becoming more adaptable. Massive growth in technology applications leading to a deeper understanding of previously unattainable variables, such as personal electronics, current account preferences, consumption patterns of households, claims histories, and earnings sources. Increasingly, more advanced, intelligent, and transparent decision-making approaches are enabled. Legitimate opportunities have arisen for firms in this new ecosystem to rethink the product/service mix, user interfaces, pricing, delivery channels, risk assessment processes, and corporate posture. As the financial services sector undergoes transformation because of data abundance, society has entered a world of financial services that personalize and refine financial decisions according to individual needs. Newly formed supply-side firms are competing with the traditional financial service suppliers.

Personalized services depict the ability to better meet individual interests, needs, and expectations by taking into account specific features of the individuals. Examples of personalization in common cyberspace activities are tailored playlists, tailored friend suggestions and news feed filtering, product suggestions, the option for users to continue watching said relevant videos on top of the suggested list, and matchmaking tools. New wealth managers will on the other hand perceive different types of data on individuals from paid service providers or analyze the publicly available aspects extensively, producing for each individual assets and tax-sensitive recommendations on product types, matching cash inflows and outflows with investment price bands. Alternatively, service providers will implement AI data mining tools that develop independently operating semi-automated services.

5.1. Importance of Personalization

AI-based investment advisors or robo-advisors made their debut with a small selection of early entrants, including Betterment and Wealthfront in the U.S. and Wahed Invest in halal investing in 2017, Osome in Singapore, and Kristal AI in India and Singapore. In less than 10 years, robo-advisory services are now under management in the hundreds of billions of dollars and forecasted to reach trillions in the next few years. These services have piqued interest among investors and financiers alike. Robo-advisory is perceived as a way to democratize wealth management, bringing it to the masses at a fraction of the usual cost, thus increasing scale. It also has implications for FinTechs wishing to capitalize on the growing retail segment. Incumbent players are simultaneously viewed as presenting a threat to the established wealth management market but also as a potential partner to build upon proprietary research, which could enhance efficiency and profitability. The various comings and goings of the robo-advisory market underscore the complexity of delivering a scalable, trusted service.

The latest generation of AI engines allow machines to do complex behavioural analysis that sifts through a wide range of factors that drive investment opportunities today; it predicts performance based on a unique current risk/reward ratio. This encourages one-person firms or whizz kids with a good pitch to garner critical mass and basis points and expands the citadel of knowledge on which investment decisions rely. Even if the bulk of AI engines out there today are not yet 'self-learning', high-frequency trading hedge funds have had three years of first-hand experience and billions to turn their knowledge into algorithmic traders. AI-based investment managers are not even constrained to traditional instruments; crypto and binary options rather than 40 years of programming experience are suddenly the order of the day.

No longer do clients hear the same thing and few get lightweight research notes to help their investment process. Seriously investment savvy clients will spend most of their time on second and third-party service algorithms that 'scrape' the right investing behaviour and run months of backtesting. This improves the standard of better-quality firms at the expense of the second and third-tier firms. Excellent research teams will be sacrificed due to unimaginative business models, while the lower cost and slow to move will attract less intelligent but faster-growing retail investors. Existing players will retrench into low-cost passive management.

And just like Blockbuster picked up VHS, Netflix will then destroy its disruptor just as credit card revenue suffocated PayPal.

Fig 4: Marketing Personalization

5.2. Techniques for Personalization

The most cited and well-known applications of artificial intelligence (AI) and machine learning (ML) in wealth management have until now been expert systems and robo-advisors. Expert systems take over the implicit domain knowledge of experts in the areas of loans, mortgages, and tax advice that can potentially be captured in rules. The knowledge gathered in this fashion can be reused and helped in the decision-making process. In wealth management, expert systems are able to analyse various thousands of different parameters and relate these parameters to each other in a way any human expert could not achieve in the same time frame while also avoiding any personal biases. The continuous improvement of these applications is difficult, slow, and requires much upkeep. Such applications fit well into the regulated world of wealth management.

In contrast, most of the recent developments in AI and ML technology focus on supervised learning with neural networks and deep learning. Non-experts have no way to evaluate the possible various architectures or the appropriateness of model complexity of a neural network as this would require expert knowledge acquired over years of application. This black-box character of AI poses a danger for the acceptance of AI applications in regulated fields. Expert systems can also be completely non-transparent. This raises ethical questions about AI applications in wealth management. In particular, complex but non-transparent applications could lead to ill-informed decisions. Also, potentially biased training data especially using generative models can simply reinforce biases.

Equ : 3 Customer Lifetime Value (CLV) Estimation

$$\text{CLV}_i = \sum_{t=1}^{T} \frac{R_{it} \cdot P_{it}}{(1+r)^t}$$

- R_{it}: Predicted retention probability at time t
- P_{it}: Predicted profit from customer i at time t
- r: Discount rate

6. AI-Driven Investment Strategies

Personalized wealth management is an ever-growing industry, especially within the Millennials and Generation Z. Startups and FinTech companies leverage technology to capture market share. Companies created the business model of automated investment advisory service powered by algorithms, in which customers' profiles and preferences were assessed with the aid of technology to offer personalized investment portfolio and management as low-cost alternatives to personal investment advisors. These services are suitable for many middle-class Millennials and Generation Z, whose disposable incomes peaked in the last decade and are expected to continue increasing while their willingness to invest is undeniable. However, the emergence of such companies raised low awareness as user-friendly technology snowballed.

Firms with the availability of deep pockets emphasized through a genuine concern for work culture and employee well-being, which is not as important for money management. With such a radical shift in the financial advisors' clientele, the semantic and semantic meaning of "wealth management" must be reassessed. With Division I collegiate athletics expanding its reach to compensate for iffy TV deals and recruiting wars raging across the U.S., the question arises — What about the wealth of Spirits? Consumers are voicing their concerns and distaste concerning this generational approach to enslaving the youth to an early payday and the Faustian decision some decision-makers will regrettably choose to partake in. Technology firms with deep pockets are involved with collegiate athletics. Companies involved with collegiate athletics are investing heavily in digital advertising, social media, or platforms providing next-generation broadcast or analytics technology.

FinTech firms can revolutionize golf's wealth management. A FinTech firm tasked with digitizing feedback from members to help the club implement cheap suggestions and upgrades would easily pay for itself in a decade. Nevertheless, such investment is hard to swallow for the country club elite, and change is annoying until it's inevitable. Similarly, a FinTech company can help students secure clout and currency from NIL deals,

helping coaches weigh players under NIL contracts against their own value while transgressing NCAA bylaws. In short, a surge in pressure and scrutiny on the staple and staple industries is coming.

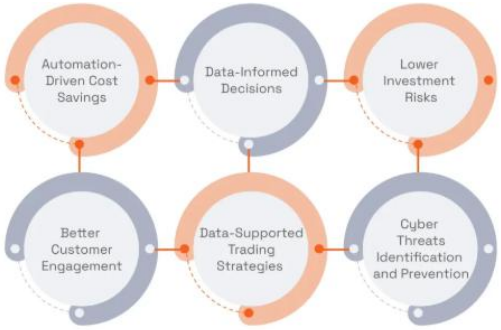

Fig 5: AI in Investment Banking

6.1. Algorithmic Trading

In recent years, coupled with the rise of deep learning methods in surging data, the impressive capacities of AI (Artificial Intelligence) and ML (Machine Learning) have transformed financial analysis into a data-intensive discipline. Although research has been mostly concentrated on analyzing structured data, the unlimited volumes of unstructured data from diverse sources, which are equally important to analyze, have hardly been investigated using state-of-art data science methods. In addition, the non-ergodicity of the market makes it impossible to generalize the results obtained in a certain market segment to other segments or time scape, making the problem exciting but challenging.

To better mimic and facilitate the study of the financial world, a simple yet intelligent simulation has been developed, where agents can use diverse data science approaches based-on simple agent-based modelling now widely applied in economics, demography and more, to make trading decisions on real/data-inspired price curves. Trained by financial investors, the agent-enrich institutional environment combined with the simulators, decision makers and realistic markets can reveal the converged behavior and emergent phenomena that impact the prices critically.

We demonstrate the pipeline by focusing on four strategies broadly-used in both mitigating fraud detection and decision-making tasks. With the need for predicting the risky stock price, sentiment analysis which quantifies the market sentiment with the news articles is crucial to boost return. By choosing the financial instrument of crypto-assets, the challenge of analyzing the spiraling price charges due to manipulations becomes a fascinating topic. A statistical arbitrage strategy based on the historical data of prices, built on the differentiation of both data sets and methods combined with prediction and signal generator. Eventually, a very accessible multi-factor model is supposed to be elucidated. It is available to the public alongside with this work and serves as a pilot for future research and applications.

6.2. Robo-Advisors

Automated financial advisors (robo-advisors or RAs) have arisen as a substitute to the traditionally more costly and less accessible services of wealth management companies. Rigid rules dictate the outline of RAs and issuing firms. Robo-advising has not yet received an official definition from either researchers or regulators. According to the majority view, the term “robo” is employed to refer to services in which a significantly reduced degree of human interaction implies that automated algorithms generate outside commentary, assess human behavior, and produce customized asset allocations. Widespread academic recognition disregards this definition’s shortcomings. To some, robo-advisors do not evolve modern professional portfolios; instead, they offer only “mechanical” recommendations on a small scope of plain vanilla exchange-traded funds (ETFs). These terms refer to online-based portfolio management solutions tailored mainly to retail investors, with European firms as examples in 2015. In 2010, two companies situated in the United States became the first companies to offer retail investment advice powered by automated algorithms; dramatically lowering costs, mitigating conflicts of interest, and enhancing accessibility. The American market is the largest and most profitable one, with estimated assets under management (AuM) in Northern America of circa $740 billion. Several factors have facilitated the international proliferation of RAs: an increasing number of smartphones and wider access to the internet have encouraged a do-it-yourself mentality and cultural changes in approaching investment.

Robo-advisors first emerged in the United States in 2010, representing a response to the numerous numbers of discount brokers and wealth management companies charged with exorbitant fees for their services when advice was rendered through the somewhat “traditional channels” of financial managers or outsourced to third-party fund managers. By this point, the RAs represented basic online interfaces through which financial managers controlled their clients’ assets; hence the label is typically employed for essentially web-based portfolio management solutions either developed in-house or white-labeled. Following growth rates of circa +150% in AuMs, scrutiny of the business model started. Several papers analyzed the “need” for RAs, claiming it resulted from the bottom of the pyramid financialization of wealth management; but that was the same

reasoning cosseting investors to trade currencies. The first wave was an exponential increase in AuM, which were subsequently augmented by competing RAs reaping the same advantages as the pioneers and banking conglomerates.

7. Risk Management and Compliance

The wealth management ecosystem has gone through various shifts over the past 30 years, from the explosion in Internet and B2B models of advice/distribution, the boom of online broking and diminution of margin/profitability of mid-tier brokers, the emergence and subsequent upswing of direct distribution, and the proliferation of ETFs/resources, etc. All these shifts have either disrupted or driven changes in the wealth management ecosystem and, in turn, the client experience. Widely cited as the biggest one yet, the emergence of AI/ML solutions and their application to WM has finally and fundamentally changed the landscape of wealth creation, storage, and transmission as we know it, approaching the end-client experience wire to wire.

This is an ecosystem poised for massive change. Three independent trends will drive this transformation. AI will finally be applied to drastically increase the accessibility, affordability, and personalization of WM services. Raw Data will be turned into reasonably priced/valuable curated, analyzed, and actionable information on which automated investment decisions can be made. Finally, the blend of the two, Access to Information-derived Advice/Decision, will be made affordable via scales. This shift to innovative conceptualization, monetization, and distribution of investment information has massive repercussions on all participants in the ecosystem; traditional financial service institutions, research providers, regulators, even policy makers.

In-depth investment and research analysis have been preserved by major financial institutions and professional research houses, pricey, illiquid and hence focused mostly on institutional clients, contributing to the widening in wealth and knowledge gaps. In less than a decade, newly minted research factories will democratize, down tube, and make it approachable even by the average Joe. Platforms fueling a Herculean ability to decode, distill and disseminate all sources of accredited information from filings/press releases to social media will massively level the playing field on which all investment professionals have access to the same raw data. AI will propel the stand-alone individual investor to leverage these insights and broaden the adoption of ETF proliferation through expensive information-rich products & services.

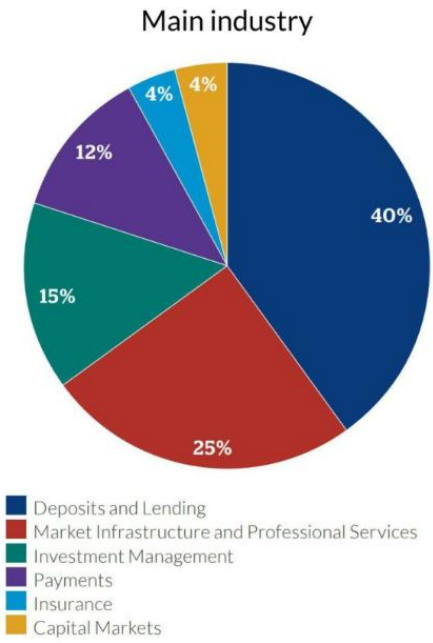

Fig 6: History of AI in Finance

7.1. AI in Risk Assessment

Until recently, risk assessment in consumer banking has been a slow-moving and manual process. For years, it was done mostly by humans reading a few pages of documents on the monetary stability of loan applicants. The entry of information technology into banking has changed this industry remarkably. Banks and other financial institutions have started capturing data regarding almost every action performed by their customers. Banks record the purchase of a gallon of milk from a store chain, while a payment for a utility bill made at a kiosk is also recorded. They are recording customers' registration of children at a pre-school, marriage, and even divorce in some cases. Every change in customer behavior and its effect on revenue is recorded. Most importantly, the most positive and negative triggers in customers' life events are being recorded. Previously considered case studies, such as changes in income, downgrading neighborhoods, and late payments, are recorded.

The interpretation of these multifaceted records is very difficult. Hundreds of millions of values on collateral and factors affecting risk assessment are continuously changing. They also differ from bank to bank, branch to branch, and even person to person. Sending that number of variables to a human for processing is meaningless. Conversely, every change in customer behavior can also be valuable in determining the stability and credibility of the customer. For instance, it is a known fact that people who have received personal loans for long periods and who are making regular payments are very unlikely to default other than unexpected life events.
To manage this increasing amount of data, banks are starting to design automated data-intelligent systems that predict future events–including events concerning defaulting. There has been considerable academic interest in using machine learning algorithms for predicting proper defaults in voluntary loan applications and risk assessment processes at banks.

7.2. Regulatory Challenges

The implementation of advanced technologies such as AI and Big Data simultaneously raises both ethical and regulatory challenges for industry stakeholders—asset management firms, their APIs, custodians, and technology/procurement vendors. Industry-wide investment in digitization is expected to double next year, amplifying the urgency of addressing issues surrounding accountability and bias in algorithmic trading. Digitization initiatives from bulge brackets and asset managers to trading venues are not merely a reaction to COVID-19 but an accelerated embrace of existing plans for efficiency gains, improved customer service, and democratization of services. As the industry becomes more digital, the new issues raised by increased reliance on data-intensive systems become pressing. Increased regulatory scrutiny is inevitable, and gaps in industry practices will be challenged more vocally than hitherto. The Race to AI is just beginning, and the industry shares responsibility to ensure this great leap forward in investing is compatible with good outcomes for clients, markets and society. The outcry over xenophobia in social media algorithms and biases in surveillance and facial recognition systems offer warnings of where unchecked industry practices can lead. The need for care and trust in designing new systems to extract and value data has never been more pressing. AI's potential to enable mass financial exclusion at one end, and direct market access for hostile state actors at the other, is another flashpoint that will only sharpen. AI is a branch of FinTech (Financial Technology) increasingly taking centre stage, creating highly sophisticated platforms capable of delivering faster, cheaper and more personalized products and services across retail banking, commercial banking, forex trading, equities, fixed income, investment banking and wealth management. AI usage in finance can be grouped into two categories. Firstly, the back-of-the-house functions, such as compliance monitoring, transactions clearing and settlement and data management. Secondly, the front-of-the-house functions such as client engagement, trading execution and investment advisory. This paper focuses on the latter in the wealth management sector, whose interaction with clients can help firms improve the overall investment experience and satisfaction levels.

8. Client Engagement and Experience

Robo-advice can assist in investing in the stock exchange. Artificial Intelligence in e-Wallet services. Fraud Prevention. AI in Financial Technologies. Current research investigates how financial consultants communicate with their customers. It focused on text as input representation to train regression-based machine learning models predicting sophistication and trust in e-finance. This research applies them to the domain of e-finance and news articles. Because NLP has proven beneficial for classification in other areas, it presents results for a combination of topic modeling and a randomized class classifier as a baseline. With increasing performance, such classifiers work for other businesses too. However, sophisticated or automated wealth management service providers have yet to benefit from performance prediction. Speaking about "robo-advisors," it was stated that they ought to learn from those platforms, following investments and algorithmic predictions rather than collections of features. Hence, research focuses on e-finance as a text domain to be gathered through web scraping. Explorative studies also aid in determining text types of wealth managers and their customers.
Online client communication bridges the gap and creates document pools. Recently, some of these communication environments have been addressed as factors influencing client trust. Existing research suggests some aspects perceived positively lead to increased trust levels in AI technology. However, academics do not address transparency and how to approach it for transparency analysis. As trust is a central trust-building mechanism, it is explored for AI in the e-finance domain. The domain requires transparency for the building blocks of trust. Financial literacy of the user group poses additional challenges.

8.1. Chatbots and Virtual Assistants

As wealth management processes become increasingly automated, clients look for banks that can provide them with advanced digital wealth management solutions while still keeping their relationship manager. This demand has encouraged many banks to create chatbots and virtual assistants that can conduct cash flow analyses, asset allocation recommendations, investment policy creation, and tailored fund searching. Indeed, several banks have invested millions in developing AI and machine learning in wealth management or launched their first digital offerings. Many respondents expressed reluctance to implement chatbots or virtual assistants

for complex advisory tasks due to a lack of skills and fear of harming their reputation. Some banks believe chatbots could only perform basic functionality, such as transmitting information, while they wished to invest effort into more advanced tools.
Virtual assistants can open up new communication channels that were previously unavailable in the wealth management industry, such as conversational and audio-based channels. This way, banks can approach the client non-intrusively by offering information instead of requesting a meeting. Existing projects were hardly mentioned. Robo Advisors offering client-initiated digital processes for retirement savings and rebalancing were mostly disregarded. The wealth management clients still seem to prefer human advisors. Many wealth managers also mentioned that current tools offered by fintechs are enough and more advanced offerings on several functionality levels, such as the ability to do cash flow planning, would significantly increase perceived added value.
An interesting session saw the discussion of live chatbots with top researchers in AI. Although such a discussion was possible, its complexity forced chatbots to refer instantly to a human expert. There was a consensus among the wealth managers that complex chats must also end with a human advisor, leading to the non-usage of chatbots or virtual assistants on a large scale in wealth management processes.

8.2. Enhancing User Experience

Wealth management has undergone a dramatic transformation in the 21st century due to increased digitization and changing customer demographics. Applications historically targeted at wealthy customers are now increasingly available to the mass affluent and retail segments, often free or at very low fees, in conjunction with massive advertising campaigns. Personal finance management (PFM), lifestyle banking, robo-advisors, and passive investment management strategies have now entered the financial services landscape. Intelligent systems are now widely used in all corners of capital markets and finance. AI-powered solutions create opportunities, but the perception of their trustworthy usage is important to make this potential work. As part of the customer experience journey, wealth management revolves around engagement and trust, fuelled by discretionary income and future prosperity. Wealth management is a high-touch service offered by qualified financial advisors or banks with wealth and asset management arms. Trust plays a crucial role in wealth management by creating symbiotic, resilient partnerships between financial advisors and clients. The acceptance of robo-advisors is largely dependent on their perceived usefulness and the customers' familiarity with robots. However, expectations of transparency are comparatively higher for robo-advisors. Adoption was further slowed down because of users' apprehension in providing digital robots with sensitive financial information and the lack of transparency surrounding the algorithms. In turn, investing decisions could be seen as less useful due to the automatic digital approach.

9. Conclusion

The digital revolution continues to rapidly transform the financial landscape, and consumers are demanding advice and services that fit into their busy lives in an easy-to-access format. Digital technology now allows financial planners and wealth managers to create a hybrid advice model that utilizes both the human touch and digital tools to scale service offerings for their retail and mass affluent clientele. The use of technology will be complemented by the human aspect of wealth management to maintain trust and relationships with clients, as understanding a client's emotional relationship with their money continues to be of utmost importance. In this equation, the role of highly skilled financial professionals will need to focus on higher value added tasks, such as imparting wisdom and industry knowledge and personalizing complex financial solutions. Hence, there is an opportunity to explore how AI, machine learning, and big data can enhance the development of personalized financial advisory services.
Financial behaviour is analysed from human behavioural and psychological standpoints. Since such behaviours are inherently complex, they can be better understood with the application of machine learning and big data technology, where predictive models are used to automatically extract high-level patterns of behaviours. A comprehensive financial plan can then be constructed around diversified investments and personalised recommendations. To further improve access to services and reduce expenses incurred, machine learning and big data technology are considerable for automated financial planning via robo-advisors. In addition, datasets pertaining to human financial behaviour in different markets worldwide can be further integrated and analysed with big data and AI technology. In this way, economic development in emerging long-tail markets can be enhanced, and the availability of necessary assets can be improved.

9.1.Future Trends

Artificial Intelligence (AI) and Machine Learning (ML) are poised to have transformative impacts on clients' wealth management processes and financial institutions. Such technological advances may, in fact, render the traditional wealth management model obsolete. Wealth management institutions are accumulating troves of rich customer data thanks to digital innovation and omnichannel access points. Financial institutions must analyze this data to provide customized financial solutions that cater to customers' personal situations and behavioral biases if they wish to improve customer-centricity. AI and ML can assist institutions in identifying

and addressing customer needs, as well as customizing offerings and services. By improving understanding, providing proactive insights on investment needs or imbalances between investments and stated goals, and considering personal preferences, these technologies can enhance individualization.

As substantial investments in security systems are made to protect such data, the demand for trustworthy, intelligent, and comprehensive personal wealth management services has never been higher. Until recently, only clients with millions of dollars to spend could afford wealth management service, but this was the result of a labor-intensive model. Due to the currently low availability of wealth managers, the wealth management industry has seen an increasing demand for alternative solutions: time-sharing wealth management services, automated investment strategies provided by Robo-Advisors, and hybrid options with asset management forms.

Research indicates that AI may be able to assist private clients with wealth management processes. AI technology, combined with big data, can integrate long-tail markets in stitching together fragmented, incomplete, and disequilibrium systems, thereby improving the efficiency of fund allocation and financial risk systematic management. Coupled with the capability of identity recognition and natural language process technology, machines may be able to completely replace laborers in mid- and low-end service fields and provide interactive services. By combining financial intelligence with AI, a "financial brain" is currently being constructed in order to provide all-inclusive financial services to meet the finance needs of ordinary people while avoiding risk management pitfalls.

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