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AI-Based Financial Advisory Systems: Revolutionizing Personalized Investment Strategies

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Abstract

Interest in Robotics and Artificial Intelligence is growing today and impacting many industries. Robotics and Artificial Intelligence have received attention and already produced the most significant results in complicated fields of services, such as consulting, law, and financial services. Today, banks, asset management companies, and insurance companies are challenged to renew their business activities more radically than ever before as the digital revolution is shaping the business environment in these sectors. Changes in the ways of delivering financial services are firm examples of this fast-paced digital revolution. The term FinTech has emerged during the past years to summarise this new technological development in finance. New approaches to finance are reviewed today with crowdfunding and peer-to-peer lending being familiar examples of FinTech. Technologies of big data, machine learning, and blockchain are also included within FinTech. There are concerns on how these new solutions are going to impact the traditional financial sector.

The impact of Artificial Intelligence is discussed regarding the digitalisation of property finance. Credit decisions, risk management, fraud prevention, trading, and personalised banking are examples of processes of specific financial services where Artificial Intelligence is applied today. Personalised banking is possibly the most profound revolution in modern wealth management advisory services. Digital investment advice is an innovation in the field of FinTech. For extensive masses of private and retail investors, automated advisory services in wealth management enormously widen the accessibility of investment advisory services that previously have required exclusive banks or wealthy familial backgrounds to afford. The advantage of these facilities is lower fees, however, costs as regards the personalised pricing of investment products might be higher.

Keywords: Automated Payroll,AI Compliance Monitoring,Payroll Accuracy,Tax Withholding Automation,Regulatory Compliance,Error Detection Algorithms,Machine Learning Payroll,Benefits Deduction Management,Real-time Payroll Auditing,Labor Law Compliance,Salary Anomaly Detection,Payroll Fraud Prevention,Net Pay Calculation AI,Overtime Compliance Tracking,Intelligent Payroll Processing.

1. Introduction

Artificial intelligence (AI) does not only impact simple tasks but also more complicated fields of services, such as consulting, law and financial services. The digital revolution shapes the traditional business environment in areas such as banking, asset management and insurance industries. The continuously developing technology has resulted in the emergence of the term FinTech, an abbreviation of financial technology. Some of the key trends in FinTech include peer-to-peer lending, crowdfunding, blockchain and personal finance. AI has found its application areas in credit decisions, risk management, fraud prevention, trading and personalised banking. Digital investment advice is a new innovation of FinTech. The possibilities that AI, more specifically robo-advisors, can offer in wealth management and investment advisory processes are examined. In advanced applications, natural language processing can be used to interpret written inputs to create analyses for investment opportunities. Algorithm-based models can compare current market data to potentially predict future market trends.AI technology combined with big data can integrate long-tail markets and mitigate information asymmetry to improve the efficiency of fund allocation and financial risk management.

Fig 1: AI Financial Advisory

1.1. Background and significance

Financial advisory services refer to a wide range of services provided by finance professionals or individuals that offer advice on wealth management. They help individuals with personal financial decisions. Generally, financial advisors earn their revenue by charging fees and or selling products (assets). The financial advisory business has several key stakeholders, including clients, traditional investment advisors, online investment advisors, and tech companies. They know the high profits generated by the financial advisory business and want to enter the field. A financial advisory service is offered by either human advisors or AI models. Traditional financial advisors keep in touch with clients to hold regular meetings, which have many drawbacks for both clients and advisors following the law of inertia. In addition, the accuracy of financial advisors' bargaining decisions depends on their previous working experience evaluating financial products without any quantitative rigidity. The situation for online investment advisors is somewhat better, generating paths of investment portfolios and letting customers decide whether to hold, buy, or sell financial assets. Although they are still qualified financial advisors that give advice to clients, the way of delivery is not conversational, chat-based, or customer-tailored.

Equ 1: Real-Time Risk Probability using Logistic Regression

$$P(\text{Default}_i(t)) = \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{n} \beta_j x_{ij}(t))}}$$

Where:

- $x_{ij}(t)$ = j-th feature of individual i at time t
- β = learned model coefficients
- Output: Probability of default

2. Overview of Financial Advisory Systems

This section provides insight into the wealth management industry's historical roots. It discusses innovations and future trends in the industry with a focus on the opportunities and threats posed by the emergence of alternative wealth managers. In addition, it provides an overview of the emergence of faster and improved analytics, prospecting, data management, machine learning, and artificial intelligence and their implications for newer forms of business models.

Advice given in written form, a personal meeting with a customer either at home, at branches in business districts or shopping venues, or via appointment at venues such as cafés, family offices, or wealth clubs continued to prosper. Small investors valued personal financial advice much like high net worth individuals did. Financial advice to private customers tended to be wide-ranging aiming for an optimal allocation of excess liquidity dispersed over various financial institutions. Childhood savings accounts, insurance products, investment- and securities accounts would be monitored, whereupon a comprehensive strategy would be sought.

These services required almost total personal discretion, till now, where for example, fool-proof methods for portfolio allocation and asset management have become available to everyone. Intelligent services embedded in banks' systems automatically detect cigarette purchases in children's accounts. Children's access to tobacco would then trigger an account freeze alert to other family members and possibly inquiry into the firm behind an abnormally high expenditure in information technology shares. Alternating black Friday fever versus 99% discounts for swords may also replace the sorting of bank statements- within account levels. These smart suggestions on how to manage wealth would soon evolve into almost human competitors in servicing wealth. On the human side, no institutionalized education or formal training exists in banks. Good and experienced financial advisers are rare and quitting advisors for competing banks is common. The latter explains why banks protect and treasure financial advisors by offering anything to keep their advisors.

Fig 2: Financial Advisory Service

2.1. Research design

To analyze individuals' experiences with robo-advisory services, we conducted this qualitative study with semistructured interviews involving customers of two different providers of this kind of service. The interview protocol consisted of 11 main questions regarding different aspects of robo-advisory services, including the reasons underlying the use or disuse of these services. With a focus on how people experienced robo-advisory services, the interview questions followed an exploration paradigm with mostly open-ended questions. Accordingly, the questions were formulated rather broadly, allowing individuals to answer them in their own words. Moreover, questions were also formulated in a way that they would be less probable to bias the participants' answers. The interviews were conducted online, lasted between 40 and 110 min, and 16 interviews were recorded via Zoom with the consent of the interviewees.

Seven of the 16 persons were stock market beginners. Five persons had small-money investments but little interest or knowledge in finance; thus, they were expected to be more open to using robo-advisors. Of these five persons, four were younger (under 30 years) students. The data set included five participants, who had previously required technical background or working experience in the finance domain, providing an alternative perspective on the subject matter. Out of the interviewees, 13 persons were identified as

Generation Y individuals, while three interviewees belonged to Generation Z. Fifty percent of the interviewees were females. Compared to more traditional, “managed” investment services, criteria such as brand name or reputation played less of a role in how participants chose among available robo-advisors. In addition to proactively conducting their investment research, they could also be passive consumers of investment services, following professional recommendations like investing in index funds. Thus, people tightly connected to the financial domain and the stock market were inclined not to recommend robotic advisors. Given this, difficulty was posed in identifying “typical users.”

3. The Role of Artificial Intelligence in Finance

Artificial intelligence (AI)-based systems will outperform traditional methods in the cases they are applied because the methods of AI leverage capabilities of computers that are not available to finance professionals. Deep learning and reinforcement learning, for example, may consider much more data in a wider variety of forms to learn about financial time series than conventional methods of quantizing observations and calibrating models. AI’s power can thus handle wide redundancies in data, while existing econometric methods rely on their parameters to predict the “test” cases. The AI often beats humans, who may be a constrained version of programs, and this is intuitive because historical trades and market data are fully included. AI funds, as complex programs which have financial observations inputted and then traded millions of times, request little discretion. In contrast, finance professionals on the floor are constrained by long speech, career risks, and the information flow between exchanges, which all stall the trading process. The strategy for individual accounts is commonly constructed by collective negotiations of a design team and trading agents, which rely heavily on experience and heuristics.

Capitalization Euler schemes calibrated with half day forward return and in-sample realized volatility are upgraded with the means of machine learning. With the price process specified, three classes of non-adaptive and adaptive trading mechanisms are learned by evolutionary strategies. The price change to investment is calculated via the equivalent stochastic control problem of the autonomous Bellman–Henstock differential equation. Under realistic transactions, it is shown that deep reinforcement learning is superior to the others in terms of Sharpe ratio and transaction cost. The results justify the purpose of machine learning, which is to capture state-action discrepancy in high-dimensional dynamic systems. Although theoretical models accommodate numerous stylized facts in financial time series, investment strategies via estimation of such models may forecast little and incur large risk. Expanding from models to pure time series with vast information, the predictive power of AI increases exponentially at the expense of a black box in interpretability and judgment..

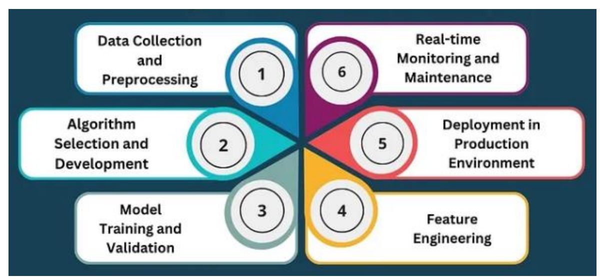

Fig 3: AI in Finance

3.1. Machine Learning Techniques

Machine learning can be defined as a family of computational approaches which are able to learn from data and provide solutions to complex problems, based on the underlying patterns from the data supplied. Various basic ML methods include supervised learning techniques, such as linear regression, classification trees and neural networks, which output some probability to predict the target variable of interest. Unsupervised methods, such as clustering, depiction of highly-dimensional datasets and anomaly detection, are designed to investigate the structure of the dataset without prior expectations. Reinforcement learning combines explorative and exploitative methods, which can be used in interactive environments to optimize some utility.

In order to apply ML, an investment decision is formulated, which takes in account all the available price information from assets globally. To improve the forecasting power of ML application, data manipulation including filtering historical prices, creating explanatory variables based on price movements and macroeconomic indicators is used to train the model for outputting some probabilities. For a given portfolio and one step in the future, based on the predicted probabilities, returns of assets are ranked and the optimal portfolio weights are calculated. Portfolio risk, drift control, transaction costs and microstructure are taken into account to fit the model for real-life implementation.

Black box characteristics of ML models reduce the transparency of the output. In addition, soaring volatility and liquidity crises can significantly lower the accuracy of the trading algorithm, which raises some serious concerns about the high frequency algorithmic trading in the market. In practice, selling positions of aggressive high frequency traders may trigger selling cascades sparking a crash. Similarly, turbulent market conditions may limit the effectiveness of ML trained models. Financial institutions are turning to the highly performative, non-linear, dynamic architecture of big data algorithms, to improve their returns through automated trading. Many of these adopters have suffered glitch occurrences generating flash crashes in which the decisions of the AI algorithms led to unprecedented behaviour of the financial market as a whole.

3.2. Natural Language Processing

Natural Language Processing (NLP) has a profound impact on financial decision-making systems by processing a plethora of unstructured text data. Financial professionals, such as stock traders and wealth managers, routinely rely on stock-specific news, earnings reports, forecasts, and social media posts. Thus, it presents significant challenges and potential opportunities to understand and leverage the unprecedented amount of information from the text. Furthermore, with the rise of both individual investors and digital media, social media text, such as posts and comments, has become an important factor influencing financial markets and deserves more attention.

NLP-powered stock price movement prediction is an emerging topic attracting growing attention due to the increasing volume of online investor-related opinions. Most existing NLP-aided prediction approaches focus on either specific stocks, predicting price changes for individual stocks, or market indices, predicting movements for index stocks as a whole. Predicting individual stock price movements is considered much more difficult yet practical considering the fast-paced movements of different stocks when major news occurs. Most of these works resort to a handcrafted model, which fetches news for the specified stocks and extracts stock-specific semantics by similarity between news embeddings and stock embeddings. Despite its promising performance, there still exist several defects including lack of news supply and solely relying on news to predict price changes.

Meanwhile, manual feature engineering hand-tuned for specific tasks usually hinders the generalization ability of financial systems. Overfitting and unpredicted ledger risks become severe problems for those systems trained by limited historical data and subjected to distribution changes. Although a few recent works propose methods to automatically learn financial text representations with text embedding pre-trained models, most of them are inferior to ordinary word/sentence embeddings in representing the financial semantics and understanding the context considering the domain-specific disciplines of financial text analysis. There exists a gap on which methods can effectively boost the performance of individual stocks auto-trading.

Equ 2: Anomaly Detection for Real-Time Monitoring

$$\text{AnomalyScore}_i(t) = \frac{||x_i(t) - \mu_i||^2}{\sigma_i^2}$$

Where:

- $x_i(t)$ = real-time transaction feature vector
- μ_i, σ_i = mean and standard deviation from user's historical
- High anomaly score → potential risk event

4. Personalization in Investment Strategies

The financial markets are increasingly complex and difficult to understand for customers. Artificial intelligence (AI)-based financial advisory systems have the potential to revolutionise the way investments are managed and create entirely new business models. Robo-advisors represent a new and missing part in the complex investment advice and portfolio management systems of financial advisors. Personalised investment strategies can help customers optimise their investment portfolios in a completely new manner and take advantage of advantages over traditional investment strategies. Furthermore, these investment strategies can be used to develop entirely new investment products that have not been possible up to now due to their complexity. The aim of this paper is to create the scientific foundation for AI-based investment advisory systems and a roadmap for building these systems. Today, customers are overwhelmed with huge amounts of options, solutions, products, and advice which all require considerable time for investigating and understanding all aspects of them. In addition, even considering all relevant factors, the financial markets are volatile, unpredictable, and intransparent structures where even the smartest investors get confused trying to predict the future. Thus, AI-based financial advisory systems are needed to help customers better understand the investment options, take fully informed investment decisions, and automatically manage and optimize investments based on the individual needs, wants, and evaluation systems of the customers.

Robo-advisors are automated portfolio management systems which create investment portfolios based upon users' answers to a questionnaire regarding their needs, wants, and potential risk. The main difference between the Robo-advisory systems lie in how the investment portfolios are created and/or maintained and how strictly the portfolios follow the goal set at the initiation. A new type of swallow the wisdom of advanced investment managers and a complete risk model based on the portfolio management rules of academia. AI-based financial models continuously adapt their investment strategies to maximize returns and reduce risks.

Fig 4: Personalization in Investment Strategies

4.1. Understanding Client Profiles

In the digital age, plenty of online financial advisory systems (robo-advisors) are emerging across the globe providing automated personalized investment strategies to their clients through means of technology. The aim of this text is to describe various digital financial advisory techniques, focusing on a financial advisory system developed at the University of Jyvaskyla in Finland. Firstly, research studies related to AI-based digital on-line financial advisory systems are reviewed. Then the background and structure of the AI-Based Financial Advisory system is discussed in detail. Finally, conclusions are presented.

Digitalization and Artificial Intelligence (AI) have increased the speed of service innovation and enabled the offering of digital services in a hassle-free manner for end clients. Several industries are experiencing disruption and transformation driven by AI. This is also true in the banking and financial advisory services industries. Modern technologies provide new opportunities for different applications. Automation of various customer processes, savings and investment management, and customer communications is growing. On the contrary, automating financial advisory systems, especially for private customers, is still in its infancy level. The most straightforward and commonly developed digital advisory systems are called Robo-Advisors, which emphasize automatic asset allocation processing and portfolio management systems.

Clients involve crossing a threshold in which banking services are different from the traditional way. The growing numbers of Robo-advisors are enabling front-end services, where clients could assess their profile, risk attitude, and goals via online questionnaires in order to receive investment accounts matching their situations automatically. Nevertheless, there is a willingness to utilize advanced technologies, proprietary know-how, and AI in developing new financial advisory systems catering for both financial planners' and clients' needs. This text focuses on financial advisory systems constructed as AI systems. The system collects clients' profiles via a combination of potential profiling/risk-attitude related questions and conventional reporting through an interactive client interface. Then an AI-based client profile modeling is made, distinguishing many segment levels, multi-layered sophistication levels, and classifying various consumer groups. The profile inference and automation process is conducted in the background, except for initial setups. At the end of the advisory, a detailed report is delivered to the client.

4.2. Risk Assessment and Tolerance

Risk assessment and tolerance is an important step in the investment strategy formulation process. Understanding clients' risk limit and appetite is of utmost importance as it allows advisors to recommend security allocation ranges that fit clients' circumstances. To match clients' risk profile with the right investment strategy, risk preference and aversion inputs have to be together used in a rigorous mathematical model which allows for purely quantitative performance and risk benchmarks. Such a model provides the ability to check with results across various time horizons the efficiency and stability of the investment strategy, including every required fairness in portfolios recommendation dynamics. Moreover, the fitting of a Risk-Return rule is a crucial advantage created by this algorithm over traditional Financial Theory. This section of the stock selection and real portfolio optimization problem description will first, in a general manner, present considerations about past and current market conditions together with insightful general knowledge about comovements and trends of historical securities' performance. Next, the risk profile of the portfolio will be presented and the mathematical models around it will be detailed. Finally, adherence to the client's risk profile will be commented on through regulatory measures. Recent market turmoil shows time smoothness and a great instability of cross-correlation structures, with extreme values of the sample negatively affecting the out-of-sample forecasts, and with the risk arising from the interdependence of economic agents and increased reliance of mean-variance frameworks. Consequently, managing such types of commovements and performing multi-period forecasts are crucial. However, given the numerous aforementioned past events that proved traditional models suboptimal, the automatic adjustment by on-board optimization agents of a static multivariate autocorrelation matrix might not guarantee the neutralization of investor sentiment influences. Besides, even setting weights by the average covariance matrix of a fixed rolling period with neural networking does not eliminate the underperformance. Therefore, a universal strategy to set an ad-hoc behaviour pattern of all security reactiveness and create dynamic portfolios tokens is needed. This bespoke implementable algorithm sets each security weight in the portfolio by tweaking in accordance with historical data the accuracy of expected returns and out-of-sample performance of traditional forecasting and optimization models. It has been designed to be equally fitted between different strategies.

5. AI Algorithms for Investment Decision Making

There has been a surge of work investigating AI applications in many domains over the past decade. In the financial area, while it appeared to be competitive and one of the pioneers of technological innovation, only a limited number of AI applications have spread out in real life. Investment portfolio management is one of the areas where AI applications theoretically fit well for its high dimensionality and complexity, but actual implementations remain scant to date. Moreover, how well AI or quantitative approaches work in portfolio management in real life is yet to be thoroughly evaluated.

Investment decisions form a complex research field of interest in finance, economics, management and psychology alike. The task of creating a model for predicting the price changes of a time series, based on its own past, is considered a classical benchmark problem in time series prediction or forecasting. As such there is a multitude of general and finance-specific prediction algorithms available for solving the problem. A feature which distinguishes between the competing predictors is their forecast horizon: they are either one-step-ahead (1 prediction) or multi-step-ahead (many predictions). While both types are of interest and indeed there are pros and cons to both approaches, the former are usually preferred in model comparison experiments.

Based on a continuous time model, which is viewed as a natural candidate for such high frequency settings, a Bayesian multi-step-ahead method is proposed where input features are chosen based on domain knowledge. It is shown that this technique is able to make price revisions for a dozen of days ahead more successfully than simple historic average price baselines, various physics inspired approaches and even relatively advanced time series classifiers either one-step or multi-step-ahead. This study offers new insight on applying AI to finance and also methodological ideas for making portfolio management observable to algorithmic scrutiny.

Fig 5: AI Algorithms for Investment Decision Making

5.1. Predictive Analytics

Predictive analytics is a complementary technique for investment advisers as it builds further upon historical data analytics. Among all prediction techniques, one of the most widely known and investigated types in the finance domain is intelligent data-driven predictive modelling. This prescriptive analytics approach builds further upon an analysis of historical data, providing probabilities of future data. In the investment domain, this means predicting future returns in investment assets. The aim of this predictive modelling is not to maximise the return or to minimise the risks but to assist human advisers in the portfolio selection in the investment advisory process. The predictive method researched is a hybrid ensemble model. This model combines a large number of reader models that monitor the deviation of the expected value as compared to the anticipated value. The ensemble combines models whose predictions agree with a majority vote. This research shows that the hybrid model can exploit all available historical data and provide predictions in all conditions. Furthermore, it can adapt to a changing environment in predicting returns while building only a few reader models. This modelling approach is generic. In addition to predicting returns, it can also be used in other datasets with a varying prediction horizon where only timestamps of data are available.

Predictive analytics is one of the most studied applications of AI in the finance and investment domain. Given abundant historical market data, predictive modelling provides probabilities of future returns. These probabilities can be used as extra inputs to improve the advisory services of investment advisers. Early works on prediction in finance mainly concentrated on simple models applied on short time horizons. Simple models are found to outperform complex models, probably because of the noisiness of market data. A more recent survey identifies data mining techniques that make predictions using complex models. The application of these complex predictive models is evolving in tandem with advanced computational power.

5.2. Portfolio Optimization Techniques

The markowitz mean-variance portfolio optimization model introduced in the 20th century is perhaps the most famous mathematical model in finance. The problem can be described as selecting a mixture of securities to be held in a portfolio with given weights. The decision variables are the weights of securities, the objective function is to minimize expected losses or to maximize expected returns subject to volatility constraints, and other inequality constraints are the requirements on the weights (sum to one, no short-selling, etc.). The model requires expected return and (co)variance (risk estimate) of assets which are usually estimated using historical data. It is intuitive to make the function less research-sensitive by employing other (co)variance/volatility measures that compare ranked portfolios. Such measures are captured by higher-order central moments or other quantile measures. Likewise, it is intuitive to make the uncertainty sensitivity function less statistical by employing distribution functions. Such should be estimated from historical data using non-parametric or parametric methods. These optimization techniques can be employed at all stages of portfolio optimization (asset selection, asset allocation, and rebalancing). They do not or only marginally require market and decision theory parameters estimation (e.g., user-defined set of assets). Instead, correspondence measures such as ranking or probability (max unlikely gain or max probable gain) are directly modeled and optimized.

Besides the discrete choice problem (asset selection), portfolio construction, optimization, and management challenges have been extensively tackled using rather uniform metaheuristics in a single discipline. These metaheuristics offer much more flexibility in problem formulation than classical optimization approaches. Firstly, the model may be richer than the mean-variance modeling (e.g., it can incorporate the mixed-form, multi-predictors, long/short, and any a priori historical/prior preference structures, finesses). More importantly, the optimization problem may be non-convex (the weights of unrestricted assets form a convex set as opposed to the reasonable constraints on the weights of the assets) and/or involve combinatorial optimization (asset selection problem). Though they globally seek an optimum, heuristic methods may compromise the well-known optimality of the received solution (non-convex problems can have many local optima). Heuristic methods optimize more efficiently and find relatively high-quality solutions, especially at early stages of searching. De facto brands of the state-of-the-art mathematical programming solvers are employed in specific problems. An extensive survey of tenant-specific, classical and heuristic, optimization methods for generic portfolio optimization can be found.

Equ 3: Credit Score Computation Function

$$\mathrm{CreditScore}_i(t) = \alpha_1 \cdot \mathrm{PaymentHistory}_i(t) + \alpha_2 \cdot \mathrm{CreditUtilization}_i(t) + \alpha_3 \cdot \mathrm{DebtToIncome}_i(t) + \alpha_4 \cdot \mathrm{RecentInquiries}_i(t) + \alpha_5$$

Where:

- i = individual
- t = current time (for real-time monitoring)
- α_j = AI-optimized weights learned via gradient descent or similar
- Each input is normalized and extracted from transactional data streams.

6. Data Sources for AI Financial Advisors

In financial services, AI-based advisory systems are starting to emerge. Client specific data, such as risk and return expectations, investment horizon, preferences regarding investments in ethical companies, etc., are needed. This is usually the same data that traditional advisors collect during a meeting and captured in a client questionnaire. Relying on a set of rules these data are then converted into investment strategies, which if accepted by the client are executed in a portfolio that is constructed accordingly. Similar client specific data are needed by advising systems as well, so that a correct investment strategy can be elaborated. The first systems that have been developed and tested focus only on some of the aforementioned data. Other systems need client portfolio details and/or broader market analysis. But systems continue to be developed and in the future more comprehensive and complete systems will emerge. Legacy assets and portfolio turnover considerations, which are considered hurdles in traditional asset management, will not be problematic for these new systems. They do not think about portfolio composition, this is an evaluation process. The outcome of the reasoning process is an acceptable investment strategy. Important to keep the system relevant is a well-functioning upgrade methodology. Significant differences are indicated between cloud and authorised location based advisory systems. In cloud systems clients' data is placed on remote servers which may provoke privacy issues. In cloud systems, all input and output data is managed by one service provider which may invoke unforeseen dependencies. In case servers of the provider are disabled for a period of time the system will be non-functional until recovery. For deliberative reasoning based methodology results are always generated. Bringing the system to an abrupt end during heuristic reasoning may lead to an incomplete analysis. Another relevant issue is service provisions and costs. In 2030 it is expected that T40 wealth managers worldwide will exit the industry or reduce their wealth management business focus considerably, as personal wealth continues to migrate to digital venues.

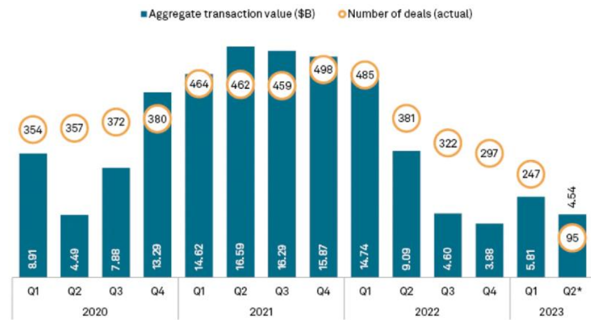

Fig : AI for Financial Advisors

6.1. Market Data

Market data is crucial for building up a reliable and trustworthy financial advisory system. There are widely available cloud platforms that can be used to retrieve the required data from stock markets. Most of the market data can be used from NASDAQ and other stock exchanges around the world. For retrieving the market data, the stock ticker symbols of the equities to be collected are required. In deep learning models, the daily OHLC-Volume (Open, High, Low, Close, Volume) is often used for training the model to predict the closing price of each day. Apart from historical stock price data, other financial variables need to be collected from financial exchanges, finance portals, fundamental companies, etc. There are plenty of data points used in this model such as P/E (price to earnings) ratio, P/B (price to book) ratio, dividend yield, gross margin, ROA (return on assets), ROE (return on equity), and each variable is extracted from affirmed databases. Getting Historical data using finance API, getting fundamental data using Alpha Vantage API key and data collection from the web all combine to compute and keep the financial model updated with the latest data.

A neural network technique called LSTM-RNN (Long Short-Term Memory network) is widely used for batch and streaming time series data. Time series data is one of the prominent data types, and it finds its applications in many financial fields such as stock price prediction, financial forecasting, and algorithmic trading. LSTMs can capture periodic patterns within time series data and other temporal or sequential dependencies. By limiting the memory effect, LSTM networks put generalized robustness on input data. Layers of LSTM memory cells in the network can learn the relationship between prices and/or the periodicity of price variation . A trained LSTM model is used to generate predictions of market evolution. This model is formed by encoding state variables and estimating the price of a financial asset in the next time period over a ten-step horizon. The output is a vector of ten continuously discounted prices, with the last element to evaluate (Real Price 10,0) of the horizon. The model is implemented by Keras with TensorFlow backend.

6.2. Alternative Data

The investment advisory systems discussed in this paper understandably rely heavily on data to provide personalised strategies to customers. There are numerous types of data in the possession of companies, but this section is limited to the most common investment databases. Market data is the basis of all financial analyses. Reading and interpreting charts is one of the simplest and most common methods of analysis, referred to as technical analysis. Market data is widely available and easy to access. It includes market prices for stocks, FX pairs, and other traded assets, along with underlying information, such as corporate news and economic news, etc. Some companies generate analyses from this data to provide investors with insights. While investment advisory bots also need news articles, whether they are scheduled news data or news analyses affect how the bot uses the information. Event-driven investment strategy research often focuses on specific events, such as mergers and acquisitions, spin-offs, earnings reports, etc., which can also come from other sources, such as text analysis of news articles. Not assigning these disclosures to a specific target date instead often leads to a weak signal that would not withstand filtering by secondary criteria. Therefore, such strategies may have lower performance in general.

Not all events provide clear information for a specific traded asset. There are numerous online portals where individuals share their views on financial topics and assets. While these writings may not give signs for sure price changes, text analysis can provide a quantifiable measure of the opinion in a community, and systematic scrutiny can help detect such gatherings; some bots do indeed steer investment strategies based on this data. It is becoming increasingly applicable that the bot classifies and weighs the texts before establishing the trading algorithm and building the modelling around it. With the advent of cloud technologies, many spend considerable sums on account datasets, making it relatively easy to determine the average sale-and-buy ratios of stocks.

Lastly, machine learning has emerged as a promising tool for wealth management. ML's widely publicised advantages include increased speed, less need for preparatory work, and the ability to process data from a vastly wider source. Nevertheless, central banks have taken initial steps to ambush the technology. Still, despite the red flags, crowded trading platforms continue to support statistical arbitrage with no regard for alpha number two or three, as demonstrated by the pressures experienced during the Covid outbreak. All of these possess numerical evidence of tactical perceptions and not the actual fundamental parameters. Data can hedge boundaries from cumulative database modification or help detect assets with similar characteristics This data category can therefore be characterised as two-dimensional: firm characteristics versus time horizon for parameter evolution.

7. Conclusion

The financial advisory sector is experiencing a notable evolution. Such transformation is mostly driven by the advent of a sophisticated technology offering, artificial intelligence (AI). In this context, AI refers to the computer science domain that deals with intelligent behaviour. Moreover, AI concerns a computerised technology that processes a huge amount of data with minimal human assistance to produce meaningful new data or to predict unseen sample data.

The implementation of AI in providing financial advice is in the form of AI-based financial advisory systems, offering extended possibilities to improve financial systems and to generate unique products delivering intelligent behaviour. In particular, AI-based financial advisory systems will bring and extend several advantages related to personalisation and accuracy of investment advice built on consideration of combinatorial modelling of evaluation criteria. Moreover, AI-based systems are proposed and presented in detail as well as models and algorithms generating unique investment portfolios.

The newly developed AI-based financial advisory systems are implemented in a form of applications that concern the domain of personal finance advising clients' investments in time-locked and risk-averse commodity portfolios. Clients are advised based on modelling their unseen financial preferences, conditions, and opportunities. After introducing the problem, assumptions, and applicable terminology, investment portfolios are generated based on considering a diverse number of stock options, with allocation amounts and duration defined by clients. At a higher level, investment portfolios concern stock assets. Hence, during the portfolio time limit, an adoption action to avoid financial losses can be taken or basic stocks can be sold. New stocks can also be proposed instead of the sold ones or kept portfolioed. The advisory system is able to update information, advise existing and new investment opportunities, and refuse wrong proposals based on financial criteria.

The model of AI-based financial advisory systems grounds a method for capturing the extensive temporal changes of financial assets, allowing comparison with predicted ones, and identifying which changes cause financial activity execution. The algorithm of the intensive financial database scans any number of temporal changes in the activity space. Such understanding offers considerable advantages, such as awareness about activity execution triggering situations or advising new investment portfolios that avoid undesirable behaviours, as well as it raises ethical considerations and privacy concern questions.

7.1. Emerging Technologies

Artificial Intelligence (AI) has a remarkable potential for individual investors. Most financial and investment services still lack utilising the possibilities offered by new digital technologies. On-line investment platforms are still rare, whereas AI and FinTech-based innovative solutions have revolutionised the wealth management industry in other markets. This paper investigates how AI, especially Natural Language Processing (NLP), can impact individualised and personalised investment advisory services as a real-time wrapper of the investment process.

Wealth management can be defined as managing the investments and financial services of ultra-high-net-worth (UHNW) individuals and families. Currently, wealth management systems utilise AI-based digital technologies on a very rudimentary level, mostly complex self-learning algorithms in trading-side. Other innovations such as NLP-based bot systems, robotics advisors, or a tailored client investment advisory systems that can largely automate real-time portfolio management are still rare. The market of personal finance management solutions is very fragmented and highly competitive worldwide, although solutions based on fixed rules without any individual adaptation are available. The first generational advisors are product recommendation systems cooperating with the existing distribution channels, which recommend financial and investment products based on past patterns as well as the input information of financial and social objectives in a non-real-time setting. However, these first-generation systems do not quite fulfil the definition of a personalised investment adviser such as banks or wealth management firms.

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