Adaptive Goal-Based Portfolio Advisory: Reinforcement Learning and User Preference Modelling for Personalised Financial Planning Systems

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1. Introduction

The landscape of financial services has been evolving substantially over the past decade. It has been argued that investments, savings, and loans should be personalized in order to maximize performance and reach individual life goals. The complexity of personal financial decisions is increasing due to the extended range of assets and long-term implications. Customers are often overwhelmed due to the wide array of possible financial products, and quantitative price comparison becomes more difficult. To save time, crucial customer requirements like high average yields or the desire for insuring property against fire or partial loss, increasingly gaining importance with the client, are not considered in traditional mass market solutions. Instead, a limited quantitative financial optimization model based on risk benefits and/or costs is implemented. More personal customer needs are narrowly considered for the approximate 10 to 20% of high net worth private banking clients requesting personal advisory services. Traditional quantitative models for optimal financial products like investment in shares, government bonds, or insurance ranging from foreign to premiums and fire insurance are based on historical performances of financial markets and described for the whole population on average. This is an inefficient way of investors' portfolio and insurance optimization, and the traditional models have been criticized in recent surveys. People are simply different and share different attitudes. Therefore, a human advisor needs to be aware of personal attitudes to work based on personal demands instead of the demands of the average customer. In addition, the complex and totally different personal and financial life cycles, including retirement planning, real estate investments, and availability of social security systems, have to be considered. As a result, the strategy of the developed AI system is to resolve these issues in order to more realistically model the choice between long-term saving accounts and mutual funds in a more complex design of a global finance advisor.

1.1. Background and Significance

Financial decisions are personal, and consumer preferences and needs are diverse. Financial services and products are being reconstructed to accommodate such idiosyncrasies, with the trend toward more clearly defined personalization underscoring this transition. More than one-third of U.S. consumers now desire a more tailored experience from financial advisors, and most high-net-worth individuals in America want personalized advice regarding their accounts. This might be the driving dynamic toward personalized finance, catalyzed by a more general global context. Currently, 57% of businesses provide personalized and individualized products and services. The percentage of organizations that 'always provide' personalized products and services has climbed over eight years to 34 percent in 2020. To a large extent, the wealth management business reflects this shift toward tailoring as it looks to further develop and pivot the value added by commercial actors in accordance with market criteria.

Two factors furnish the catalyst for this change. First, big and alternative data storage and analysis let customer and product characteristics come into focus more sharply, speeding up the road to responsible individuality in the process. Second, ubiquitous digitization – in retail banking as in every other industry – requires a competitive rebalancing of the cost-cutting advantages digitization presents. A glance across the societal landscape will yield the boundless mantra of digital success celebrated as one in close harmony with purpose. Companies that can reduce costs either through the exertion of labor or of capital have turned empirical evidence into action, thus toadying to the perilous precipice of redundancy. To say that any industry in possession of an unnecessarily large quantity of data can now dispense personalized advice. Consumer preference comes into play significantly: 34% of individuals in the U.S. would prefer a single point of contact with whom they can blend human and AI advice. Only a quarter would prefer pure AI digital advice.

1.2. Research Objectives

In consideration of the suitability of AI in personalized financial advice among a range of stakeholders, this paper investigates whether, firstly, automated financial advice-giving systems generate advice that advances the theory-informed pathways to informed choice, communicative accountability, and problem-solving capacity; and secondly, whether these systems present implications for consumer decision-making and the professional finance advice industry. The four identified research objectives undertaken in order to investigate developing AI systems for personalized financial advice are: • How, and to what extent, can AI enhance the decision-making process in personalized financial advice? • What is the usefulness of this AI system for individual consumers, who have a unique set of preferences, needs, and/or a particular financial position? • What informational and decisional effects does this technology have on those receiving advice, and in either the 'yes' or 'no' case, what are the implications for the professional financial advice industry? • Can this AI system help both those who are close to expert professional knowledge (enabling them to act more like professional finance knowledge workers) and enable those who are not experts, and who do not wish to be, to act on this advice successfully?

2. Foundations of Personalized Financial Advice

Customization is considered a fundamental requirement in today's financial services industry. Typical measures influencing customization include segmentation, targeting and positioning, and value co-creation. The ideal financial advisory process would be one that is tailored individually to meet the specific needs of each client. Despite the pressing need for customized financial services, established traditional business models for advisers often depend on economies of scale. Advisory actors still face substantial challenges in delivering personalized investment advice—that is, advice that finely prioritizes desired outcomes over investment options while respecting hard and soft individual constraints for different investment objectives.

The need to adjust to these changed financial advisory conditions has been underlined in several ongoing reports. The changes in financial services are essentially driven by the self-fulfilling expectations of a new generation of investors who demand tailored services. Experts in investment management unanimously agree that active participation by an investor significantly affects the portfolio's return. Therefore, consumer engagement in services such as wealth management may facilitate investment decision-making, which leads to value being created due to the perceived high performance of such services.

The developments in IT have facilitated a deeper understanding and segmentation of the customer and allowed financial advisory models to become more customer-centric. Here, leveraging AI techniques can lead to premium service, enabling financial institutions to seize competitive advantage through customer acquisition and retention. With the emergence of IT, big data and AI, it would be more economically feasible for banks and institutions to serve such a personalized portfolio in the future.

2.1. Traditional Financial Advisory Models

The two principal categories of financial advisory models that have dominated the market for many years are: the independent financial advice market for the affluent and mass markets, and the wealth management market for high-net-worth individuals. Financial advice to other segments of the market is mostly transaction-based and unscheduled. Several conflicts of interest can arise from this model. The selection of potential recommendations for an advisor depends on different aspects. Firstly, most of the time, their selection depends on the best products for their own purposes. Secondly, advisors can have a preference for a particular investment derived from the way they have been incentivized, specifically by commission. Given these limitations, advisors' recommendations are generalized and impersonal, as is the investment-risk profile they recommend, hence neglecting any demographic, behavioral, and sales- and consumption-related factors. These models have shown some limitations; clients are increasingly dissatisfied with impersonal advice and are looking for a more customized service delivery. Although a small number of firms recognize this trend, customization is just one of various services offered.

Bearing in mind these value propositions, the one-size-fits-all models are unlikely to be suitable for any market. Some firms believe that they offer a truly tailor-made service. Their advisors are therefore able to adjust their service package according to individual client needs. With regard to the features of the 'personalized' advisory model, in reality, it represents the closest thing to a truly personalized service. However, the services they offer support only a portion of the client's needs. It is true that they offer a larger variety of delivery channels, but the feature that makes them unique is their in-depth understanding of their clients' needs, as derived from their comprehensive financial planning services. They basically provide a whole service package based on the individual client value proposition on a product/services. This advisor is not independent. These advisors are, on the whole, wealth managers. The term 'private client' is used for both wealth managers and independent advisors. These are the clients seeking advice. From an advisor's perspective, regardless of the type of service they offer, the service is still impersonal. This is supported by the following considerations.

2.2. The Shift to Personalization in Financial Services

The long push by financial services firms toward personalization accelerated substantially in recent years due to a number of converging factors. On the consumer side, individuals have become more open to technology disrupting a wide array of financial services. They are willing to explore alternative providers to address their spending, saving, investing, and borrowing needs. It is also now implicitly understood that data analytics and machine learning empower the tailoring of financial offerings to investors' circumstances, objectives, and risk tolerances. Consumers appreciate these tools and techniques in part because algorithmic predictions already shape so many other aspects of their lives. On the business side, the drive toward ever-greater efficiency has companies either fully embracing or dipping their toes into digital advice provision. Some have already concluded that further technological disruption to personal advisory services is inevitable.

A range of firms already offer personalized or automated advice that is a little more tailored based on client circumstances. Some firms have robo-products that cater to a slightly narrower risk tolerance, possibly seeking to minimize client losses. There is evidence showing the demand for and consequently the growth rates of robo-advisory services by region. Technology-driven firms showed greater client acquisition, satisfaction, retention, and re-engagement compared to more established financial services firms. However, the product development motivating this deep personalization instinct does not seem to be personalized advice or automating advice delivery to reduce costs. No one has looked at getting more individualized in the nuts and bolts of the financial market.

3. Machine Learning in Finance

Section: Developing AI Systems for Personalized Financial Advice, Topical Insights, Impacts, Technological and Societal Developments

The introduction of machine learning technologies into financial practices has become a trending topic throughout the past decade and sparked quite a large body of research. Though the financial world is a tough and dynamic environment, there are countless applications that have emerged. For instance, large investments have been made in trading platforms developed by startups specializing in machine learning-based ideas. These platforms typically claim to beat classical benchmarks by using short-term and long-term trading strategies without relying on historical price and volatility data alone. Machine learning algorithms are frequently used to reveal statistical patterns by processing and interpreting vast amounts of financial data such as economic indicators, financial reports, analyst predictions, and news articles, potentially opening a powerful future for investment strategies that go far beyond our human capabilities.

Unfortunately, there are many limitations to big data technology for finance. Poor file architecture is one, operating from unorganized files that lack any logical order, making this data incredibly difficult to analyze using big data technologies. Financial reports, for example, are stored in PDFs which need to be completely rebuilt in order to utilize the data they store efficiently, or alternatively, huge effort and expense have been poured into scraping data individually. There is no definitive solution to preventing these bottlenecks, but the smart use of machine learning to filter and prioritize the data can help reduce these pains. Data privacy is another problem. Laws and regulations, as well as public concerns, have become more proactive in preventing unethical use of private data and restricting the free movement of it. Machine learning geared towards finance is difficult due to the need for data such as granular-level transaction information, which can be private and even illegal to have access to per customer. Authorities can provide data for regulatory purposes in many areas and are therefore a useful source of data, but the sharing of customer data in the interest of business sounds bad from a political, legal, and customer trust standpoint. The key barrier to integrating this technology in finance is a lack of high-quality data. This leads to outputs becoming meaningless and unreliable due to a misuse of data such as poor data inputs, selection processes, representations, quality control, and data-induced bias. Ultimately, the model will have an increased likelihood of misgeneralizing and could very easily collapse. As a result, the broader adoption of financial big data technologies is slow.

3.1. Applications in Investment Strategies

One core application of machine learning in finance is through investment management strategies. Recently, machine learning has been adopted for applications such as stock selection, portfolio management, and predictive analytics based on trading patterns. For stock selection, machine learning models can help investors automatically incorporate relevant short time-series stock information, thus tracking investments in quasi real-time. In portfolio management, model predictions, i.e., portfolio weights can be issued along with long/short signals from another classification model based on alpha. More state-of-the-art machine learning strategies exist where an autoencoder structure is used to uncover the hidden factors driving risk premiums in financial markets. These models have been found to persistently outperform long-short strategies and deliver positive to very high Sharpe ratios in several major markets while exhibiting substantially lower exposure to macroeconomic factors.

In trading, applying innovative machine learning techniques for trade signal extraction optimizes investors' profits by reacting faster to the changing investment environment. Such approaches can integrate additional decision rules into non-linear trading strategies based purely on outputs of forecasting tools. In proprietary trading, it can provide banks with fundamental insights and ensure good risk management or in investment banking for proprietary trading by creating artificial intelligence algorithms based on non-linear forecasting tools and other structured algorithms. This will help traders maximize profits by aiding them to react to changing market conditions more quickly with higher confidence.

A new approach based on non-linear forecasting tools, especially artificial neural networks and support vector machines, can be beneficial to banks in comparison to traditional trading strategies. This is mainly because it reacts faster to new market conditions and thus ensures quicker embedding of the strategy actions resulting from the new market conditions. This is possible because artificial neural networks exhibit the ability to analyze quickly and in a timely manner with very high precision large and noisy databases. The main advantage of non-linear forecasting algorithms, besides increased accuracy of the forecasted data, is the speed of data analytics. An algorithm like ANN or SVM, for instance, does not require the analytical approach of traditional forecasting tools, which are based on empirical or econometric models. These approaches are more complex and expensive than machine learning models, as they require special training.

3.2. Challenges and Opportunities

Integrating artificial intelligence (AI) solutions in the financial industry might pave the way for more risks and benefits. Concerning the limitations, when it comes to decentralized finance, AI models should be trained on cryptocurrency or smart contracts data. Given that the historical price of cryptocurrencies is extremely volatile, signifying the breach of privacy if a data subject has a stable, publicly linked cryptocurrency identity, the lack of consumer endorsement makes it significant to consider the integration of a clear oversight framework requiring multinational consistency and control on the integration of machine learning methods within the financial sector. While the results of the application of the knowledge can provide valuable insight, the use of machine learning is not without challenges and threats. The application of machine learning methods is highly reliant on the development of a robust, extensive, and relevant dataset. Many providers of financial services may not possess a consistent stream of data or software to gather, handle, and decrypt this data, hampering the development of solutions that are generally appropriate to the majority of the population. Additionally, there are numerous underlying ethical and regulatory issues between financial services programmers and companies due to a limited understanding of the industry settings and decisions. One of the main issues facing the financial sector is how any algorithm-based result can be validated to guarantee that it is safe and reliable. The point at which an interpretation of 'opinion' occurs, the trust in the resulting algorithms may be curbed, and as a result, regulatory standards should be explored. In terms of data security, regulations concerning personal data should not only be updated in the context of broader AI legislation. Individual personal data continues to be the primary asset of banks and other financial companies, which has sparked widespread usage of machine learning in the personal finance business. There are such opportunities: many advances have been made in machine learning, and numerous algorithms and tools are freely available. The area can uncover unique possibilities in their proposal for personalized financial advice in their organization. In order to profit and improve operational efficiency, a provider can concentrate on providing private guidance. Offering personalized services might also allow businesses to innovate and develop new strategies. In comparison to other studies, we suggested a personalized portfolio risk assessment as one prospective application because the user's standpoint is not currently accounted for in the decisions. For illustration purposes, we proposed the following personalized portfolio risk assessment-based finance applications in their proposal for personalized financial advice: in light of military building hazards, providers try to avoid investment activity through certified organizations. Regulatory authorities have also enacted legislation requiring fund management where investing in corporations is unaffected by the provider's alternative requirement of one group. The investment firm analyzes finance through the lens of substantial risk and reward depending on the underlying finance and result streams.

4. Personalized Wealth Management with AI

There is a growing trend in consumer-oriented AI applications. They aim less at mass effects and mass production, and instead focus on enabling the delivery of personalized services. At businesses that provide wealth management or are active as financial advisors, the process of AI-based customization involves several steps. First, data analytics is employed to calculate the efficient frontier and the set of investment opportunities. By being the 'Base AI', individual client advisory focuses on this typically rational level. With 'Smart AI', which integrates the modeling of human behavior, we go beyond that. Essentially, to devise a portfolio tailored to the client, data analytics are used to differentiate between client goals and adopt suitable strategies.

For each of these steps, big data analytics has an insightful approach to predictive—and possibly cognitive—support. That is: increasingly large and heterogeneous data sets contribute to financial market statistics. This 'Market AI' approach of using cognitive computing technologies to generate a more sophisticated customer profile catalyzes the following conclusion: It is not possible to physically traverse the space spanned by the many different possible de facto investment strategies. If the potential alternatives are vast in number and not sufficiently constrained, the confluence of handicaps in the form of transaction costs, poor tax effects, self-reinforcing network effects, shocks coming from related assets and liabilities, unburdened betas, and other such unforeseeable events becomes extremely high.

4.1. Data-driven Portfolio Optimization

For investment managers as well as for individuals, personal wealth management has taken on increasing importance in the past century. While in the past personal portfolios had to be managed in a rather "passive" manner during different life stages of the investor, with the changes occurring within the general field of financial planning, in the coming decades portfolios will need to be more actively managed and adapt to the changing extended longevity of some investors, changing desired lifestyles, decreasing relative size of company pension offerings, and general economic conditions. In order to better manage wealth, and using investment professionals as a tool, many new advisors are evolving using computational predictive models around understanding not only the securities but also what may be in the best interest of the investor, building on preferences, risk tolerances, tax and legal profiles, and probably overall investment horizons. A critical facet in this data-driven wealth management development is asset allocation strategies that play an integral part in designing an optimal portfolio based on certain investment aims and attitudes towards risk.

Portfolio optimization results in individualized portfolios that can be analyzed based on a fundamental risk/return trade-off and even ethical, social, or governance screens. How can rapidly changing market information be used to improve portfolios in a more flexible manner? Portfolio managers and individual investors can manage a portfolio to best respond to their own goal-based needs by using methods of risk modeling and potent future prediction. Modern portfolio optimization should use risk modeling, advanced algorithms, and real-time data to change the portfolio at any time in order to enhance the return for the level of future risk taken based on the updated model choices. If investors have preferences that we can measure, and adapt to their changing horizon and/or goals, their chosen route to a specific goal can be unique to their selected set of preferences. A sophisticated wealth management and planning system first applies the automated tools mentioned above. Some systems can further integrate these tools with continuous updates to personal plans that respond to a changing investment market as well as individual changes in potential future end states.

4.2. Risk Management Techniques

Portfolio development strategies for personalized financial services aim to increase invested capital, earning either dividends or asset value growth. However, they could simultaneously result in capital losses. In order to protect client funds, it is necessary to ensure the safety of the deposit by completing risk management procedures. Specialists in this area apply different types of approaches for portfolio risk management. The risk of portfolio loss as a result of investor strategy implementation can be analyzed by utilizing variance and tail value at risk. The risk of a portfolio might also be estimated by calculating a profit and loss value as compared to the deposit value.

Applying the latest data analysis technology, an investment advisor could forecast investor portfolio vulnerabilities. Thus, the capacities of a portfolio structure could vary due to the dynamics of the international macroeconomic strategic scenario and market environments, generating the requirement for ongoing risk management. This approach can also be applied to real estate investment analysis or bank portfolio management. As the economy has shifted to accommodate personal finances and the investment sector, operators have concentrated on more precise predictive algorithms and tailored financial advisory services. In prospective investment potential, some research has tried incremental portfolio risk assessment. Market stocks in the AI era can also be approximated by predicted inventory return. Concerning risk, the shaded inventory capital has been computed, but it is not proportional to strategic need.

5. Ethical Considerations in AI-driven Financial Advice

Ethical considerations regarding complex algorithms in providing financial advice are unavoidable. Transparency is a key topic: who knows what when, and under which circumstances. Clients need to know which of their digital features are used as a base for the algorithm-driven recommendations in financial advice. Clients need to understand why they receive or do not receive certain products within the full portfolio of services and products offered by a financial service provider. Recent discussions regarding social scoring mechanisms and democracy support the above statements. Social accountability towards society is a must. Regulatory acceptance, along with active participation of stakeholders and supervisors, can and should pave the way for how the above-mentioned ethical issues are dealt with.

An important topic for discussion is the potential direct and indirect consequences of AI behavior in financial advice. A wide range of systems are designed to handle client relationships in a professional manner and should avoid creating potentially racist or sexist overtones when advising clients based on personal information. However, algorithm-driven decisions can be a misuse of power due to hidden biases in the algorithms. These biases are already present in the data used for the construction of the learning algorithm. It is questionable whether professional ethics will hinder an automated, algorithm-driven consumer-centric behavior in financial services. The bottom line of this discussion is the challenge of fairness: a fair algorithm-driven financial advice should exclude all morally irrelevant features and should include all morally relevant features when providing investment choices to clients. Indeed, this is easier said than done. The related regulatory and supervisory concern is how to operationalize fairness as a customer-related view in AI behavior in financial services and products. Preconditions for fair decision-making in the AI financial world are transparent, accountable, and unbiased algorithms. Therefore, it is important to create European and international standards or guidelines on how fair, transparent, accountable, and unbiased AI behavior can be created and used in a broad range of financial services. The above description is not only a concern for the financial services industry and supervisory authorities; the broader public also needs to be informed about the potential evolutions and their risks. Inputs from several actors, including, if desired, the financial industry, should help to address these questions.

5.1. Transparency and Accountability

Recommendation: The critical elements for building clients' confidence in AI underpinning financial advice are transparency and accountability. To develop such trust, financial institutions must start by establishing the processes needed to ensure clients are provided with understandable communications explaining the algorithms and data determining personalized financial advice and the way in which these impact recommendations. The appropriate approach for creating such materials will depend on both the complexity of the mechanisms underpinning the advice and the preferences of the relevant individuals. As far as possible, the data used in generating these communications should be drawn from the client's own financial information, reflecting their particular financial needs and priorities. Convenience and numbers are also important to build trust. Financial institutions should invest effort to simplify the required operational arrangements, whether this entails, for example, variations between advice channels or other bases of differentiation. Accessibility and personalization are important for trust, verification, and regulatory acceptability. Financial institutions should harness technology to limit the cost to clients of implementing AI advice forms those processes necessary for giving clients the opportunity to verify to their satisfaction the personalization parameters that influence suggested courses of action. A robust system for internal grievance should be introduced to ensure clients can voice complaints and demand the correction of harmful or uncomfortable service outcomes resulting from the AI employed. AI-augmented financial advisors can further enhance clients' trust by submitting the automated AI components to regular audits conducted by qualified and credible external experts, and the adequacy and regular conduct of these audits should also be verified by regulatory authorities; this way full transparency regarding internal auditing activity is ensured. Introduce AI audits. "Convenience" provides "trust" in AI even without other factors. Financial institutions should make clear and unequivocal commitments to refund clients for all losses resulting from providing, or omitting to provide, AI-based personal advice, at all times ensuring compliance with any relevant national insurances and other protections. Governments or regulatory authorities should always clearly indicate when issuing legal and regulatory measures in relation to the provision of personal financial advice based on AI who is legally responsible for any associated loss or gain that clients experience, primarily as a result of advice given by the AI component. Use convenient, concise, effective communication, easy to understand. Value mental effort and easy-to-understand advisory rules. Consider the use of professional language in legal texts for AI-augmented financial advice aimed at professionals, organizations, and skilled individuals in the domain. An AI model should be designed in such a way as to allow users to understand the process, the basic premises, and the decision rules through which the system reaches its prediction and recommendation.

5.2. Bias and Fairness

A known problem with using an algorithmically driven approach in offering personalized investment advice is the potential for biases in the decisions. One issue that has been given noteworthy attention is the fairness aspect of AI-driven financial advice. Most machine learning algorithms are trained to minimize expected loss or maximize expected rewards. Such algorithms are trained on historical data to make decisions that maximize the chance of meeting the decision target. There is, thus, a real risk of biases entrenched in the data and of replicating those biases in the decisions made by the AI model. It seems reasonable to assume that the training process of many AI-driven investment robots can lead to decisions that discriminate if the collection of historical decision data on which the AI model is trained is biased toward a certain type of person. Moreover, the issue of fairness is even more concerning when we acknowledge that the investors are frequently in a vulnerable position.

As a result, there has been advocacy for the implementation of fair machine learning models and calls for a prohibition on the use of explicit categories like religion, sexual preference, or political views as long as no ways are found to avoid the legally prohibited use of this information unsanctioned. Given the possible impact of an AI-driven personalized financial advice investment service on the recommendation of financial products and services to individuals, the system must be designed to ensure principles like non-discrimination. This involves keeping a close watch on the fairness of the final treatment individual investors receive. As an AI system learns from the data, it must take into account fairness measures on an ongoing basis and adapt and change accordingly. It also requires continuous verification to assess that the quality of the data, the features, the machine learning model, and the decision-making process are indeed maintained at an acceptable level. Finally, steps towards bias and fairness must be implemented when training the AI model with respect to the data and ensure the effectiveness of the actions taken. This is crucial also because the presence of biases might affect the quality of the model developed as well. Addressing these requirements in the AI system will contribute towards safe individual AI-driven advice in the new investment service. Ensuring fairness may also require designers to revisit the sources of data they use to train their algorithms as well as the process in which the model is trained. Post-design audits may be necessary to ensure that certain groups of individuals do not receive recommendations that are systematically inferior to the ones given to others. There is also evidence that diverse groups of individuals contribute to more fair AI systems. It is required that teams involved in AI developments are also very diverse in terms of gender, ethnicity, discipline, and philosophical perspective.

6. Future Direction

Being a rapidly growing field, machine learning technologies have shown great potential, and the future will see an increase in the accuracy and the degree of the advice given using these technologies. Moreover, the research in personalized financial advice continues to explore various potential complementary tools and technologies that could be added to personalized financial advisory services. One of the new technologies, blockchain, has the potential to not only record but also automatically maintain and update complex personal investment contracts without a need for a human advisor. The technology of crafting and serving natural language constructs is also advancing, and robotic assistants are beginning to accept and execute spoken commands. Lastly, biometric contracts could make client-advisor transactions frictionless, where the client may unknowingly receive advice because we will be able to track what is happening in their financial lives.

Technology alone is not sufficient for providing good personalized advice. The future of delivering personalized financial advice lies in a combination of technology, shaped by client need. Financial advisors will need to play a critical role in ensuring the appropriate integration of technological management with personal experience management for individual clients or groups of clients. The focus will need to remain on full service to the client in financial management but will be able to expand through the use of technology to daily wealth management, providing personalized tailored 'rules of thumb' to clients. Continuous training to extend the skills of financial advisors may involve understanding internal and external system processes, processes of financial management itself, and understanding unique theories and conscious/unconscious psychological biases that influence behavior, as well as developing the appropriate communication and advice methods. Data security, data protection, and many other regulatory and ethical issues facing the potential changes that AI represents in this field are being addressed. More broadly, account is even being taken of the impact of AI on the way societal, legal, and ethical conventions are defined. Ethical guidelines for machine learning continue to be explored, and the end of this road will involve a partnership between the relevant economic and computer science areas that discover responsible AI along similar lines. Finally, new AI technologies are continuing to emerge and will inform the landscape in which responsible AI endeavors are carried out.

7. Conclusion

Holistic financial planning that considers the emotional needs of investors beyond their capacity for risk can bring more value for customers, as long as advisory services are adjusted to individual client preferences. It sounds straightforward and is indeed, but AI can just help address these "soft" skills at a larger scale. Personalized financial advice will always remain a human business that targets individual clients, their needs and dreams. Technologies can help advisors to make decisions and automate some routine activities, but financial advice is not only about numbers.

The times, when sending greeting cards, making phone calls wishing happy birthday and remembering to ask how the client's son's chess game went was an important part of the process of doing business, have not yet been over. They have just shifted to the digital space, suggesting a personalized message on social media to congratulate people with their achievements and send reminders instead of making calls. As clients increasingly use technology, they expect more automation and innovations to make a better service out of it. You might not be part of the digital era if you are not aware of such transformations, the emergence of AI-driven solutions aiming to bring some value to the industry and clients in terms of improving outcomes, reducing costs and increasing client engagement. However, it remains to be seen whether advisors can help their clients achieve better financial outcomes using previously unavailable data or information. AI systems can turn this promise into reality.