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An Generative AI Framework for Personalized Wealth Management and Investment Advisory

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Abstract

The rapid development of artificial intelligence in the financial sector has driven the shift from traditional investment advisory systems to data driven, automated models. However, current robo-advisor systems still rely primarily on static investor profiles and fixed portfolio optimization models, leading to significant limitations in contextual personalization and adaptation over time. In this context, Generative AI emerges as a novel approach with the ability to infer contextual information, integrate knowledge, and generate natural explanations for financial decisions. This research proposes a Generative AI framework for personalized asset management, aiming to integrate investor data, contextual modeling, and Generative AI inference mechanisms within a unified, multi-layered architecture. The proposed framework comprises six main components including investor data, investor profiling, context modeling, generative AI inference engine, recommendation and interpretation, and feedback and continuous learning mechanisms. This framework enables the transition from rule-based financial advice to an intelligent advisory system capable of real-time adaptation and personalization. In terms of contribution, the research expands the role of Generative AI from forecasting tools to financial inference systems, while proposing an integrated architecture for personalized asset management. Furthermore, the research utilizes the technology-organization-environment (TOE) framework to analyze the practical implementation conditions of the system, thereby clarifying the opportunities and challenges in applying Generative AI to the asset management field. The research findings provide both theoretical and practical value, contributing to the development of next-generation financial advisory systems that are highly explanatory, adaptable, and personalized.

***Keywords:** Generative AI, Wealth Management, Robo-advisory, AI for Financial Analysis, Personalized Investment.*

1. Introduction

The past decade has witnessed the rapid development of Artificial Intelligence (AI) becoming one of the core technologies driving digital transformation in the financial services industry. AI in general and machine learning and deep learning techniques in particular has been widely applied in areas such as credit rating, risk management, fraud detection, algorithmic trading, and investment decision support. The development of AI has helped financial institutions improve data processing efficiency and automate complex decision-making processes (Bharadwaj et al., 2013). In the field of wealth management, the development of Robo-Advisor systems has marked a significant shift in the automation of investment advice. These systems typically rely on portfolio optimization models such as Mean-Variance Optimization and standardized questionnaires to determine an investor's risk tolerance, thereby recommending a suitable portfolio (Waliszewski and Szklarska, 2020). However, while reducing costs and expanding access to financial services, current Robo-Advisor systems are still limited in their ability to fully reflect the individual context and complex financial behavior of each investor. Furthermore, recent studies have shown that current Robo-Advisor systems still struggle to provide a high degree of personalization, due to their heavy reliance on static models and simplified assumptions about investor behavior. This results in investment recommendations that are not truly adapted to the changing financial goals, market conditions, and financial lifecycles of individuals (Khan et al., 2025). Therefore, a significant gap exists between the automation capabilities of the system and the increasingly high expectations of investors for personalized financial services.

Recently, the emergence of Generative AI and Large Language Models (LLMs) has opened up a new approach in the field of finance. Unlike traditional AI models, which mainly focus on forecasting or classification, Generative AI has the ability to infer, synthesize information, and interact with users using natural language. According to Lee, J., Stevens et al. (2024), LLMs can support many financial tasks such as analyzing financial documents, summarizing market information, and supporting investment decision-making. In particular, Generative AI is being considered a potential technological platform for the next generation of intelligent financial advisory systems. According to Yang et al. (2023), LLM-based financial models can simultaneously process structured and unstructured data, including financial reports, market news, and market sentiment data, thereby improving investment decision-making capabilities. However, studies have also shown that generative AI in finance still faces many challenges such as hallucination, lack of stability in reasoning, and risks to the reliability of recommendations

Although the potential of Generative AI in the financial sector is attracting significant attention, current research primarily focuses on individual applications such as financial text analysis, financial chatbots, or trading support, rather than building a comprehensive framework for personalized wealth management. In particular, there is still a lack of integrated research simultaneously incorporating elements such as investor profiles, individual context modeling, Generative AI inference mechanisms, decision interpretation capabilities, and continuous learning mechanisms within a unified architecture (Tahvildari, 2025) Therefore, this study proposes a **Generative AI Framework for Personalized Wealth Management**, where Generative AI acts as the central inference engine to analyze investor profiles, understand individual financial contexts, generate personalized investment recommendations, and provide transparent interpretation for users. The framework is designed with an investor-centric approach, aiming to enhance the personalization, transparency, and adaptability of financial advisory systems. This research contributes to the academic literature in three main aspects. *First*, it synthesizes the role of AI and Generative AI in asset management. *Second*, it proposes a conceptual framework integrating the core components of a personalized financial advisory system based on Generative AI. *Third*, it analyzes the opportunities, risks, and challenges of implementing Generative AI in asset management, thereby providing a basis for future empirical research.

2. The application of Artificial Intelligence (AI) in the financial industry

2.1 Evolution of Artificial Intelligence in Financial Services

The financial industry is considered one of the pioneering fields in the application of artificial intelligence due to its heavy reliance on data, the need for real-time information processing, and the demand for decision support in a highly uncertain environment. Over the past decades, AI has gradually shifted from rule-based systems to machine learning (ML), deep learning (DL), and more recently, generative AI (Bussmann et al., 2021). The early stages of AI in finance primarily focused on building expert systems to support credit decision making and risk management. While these systems were capable of simulating expert knowledge, they faced significant limitations in adapting to the ever-changing landscape of financial markets. The emergence of Machine Learning marked a significant shift by allowing systems to learn directly from historical data instead of relying solely on predefined rules (Lessmann et al., 2015). In the next phase, Deep Learning further expanded the analytical capabilities of AI by processing non-linear relationships and mining unstructured data. Deep neural network models have been widely applied in stock price forecasting, market sentiment analysis, and risk management (Fischer and Krauss, 2018). However, despite achieving high predictive accuracy, these models primarily perform pattern recognition tasks and lack contextual interpretation and inference capabilities. The emergence of Generative AI and Large Language Models (LLMs) marked a new milestone in the development of financial AI. Unlike traditional forecasting models, generative AI has the ability to understand context, synthesize knowledge, and interact using natural language, thereby expanding the role of AI from a data analysis tool to a decision-making assistant (Li et al., 2023). This shift is particularly significant for financial services requiring a high degree of interaction and personalization, such as Wealth Management.

2.2 Applications of Artificial Intelligence in Financial Services

2.2.1 Credit Scoring and Risk Assessment

Credit rating is one of the most successful applications of AI in the financial sector. Machine learning models have demonstrated the ability to significantly improve the accuracy of predicting customer default likelihood compared to traditional statistical models. In the renowned benchmark study by Lessmann et al. (2015), over 40 classification algorithms were evaluated on various credit datasets, and the results showed that modern machine learning methods outperformed logistic regression in many cases. In addition to improving accuracy, AI also helps financial institutions leverage alternative data to expand access to credit for customer groups without a complete credit history. However, AI-based credit models are often criticized for their lack of transparency and explainability. Bussmann et al. (2021) argues that the use of black box models in credit decisions can increase legal risks and make it difficult to comply with financial regulations.

2.2.2 Fraud Detection and Financial Security

Financial fraud detection is the second area where AI has achieved significant success. Machine learning algorithms are capable of analyzing millions of transactions in real time to identify anomalous behavior and detect fraud before it causes substantial losses. A systems overview by West and Bhattacharya (2016) shows that machine learning methods are significantly more effective than rule-based systems in detecting credit card fraud. However, the effectiveness of fraud detection systems heavily depends on the quality of the training data. Pourhabibi et al. (2020) point out that current models often struggle when faced with new forms of fraud not previously seen in historical data. This indicates that adaptive learning and inference capabilities remain a major challenge for AI in the financial security field.

2.2.3 Algorithmic Trading and Investment Analytics

AI has brought about significant changes in algorithmic trading and investment analysis. Machine learning and deep learning models are used to predict price movements, analyze market signals, and optimize trading strategies. Fischer and Krauss (2018) showed that Long Short-Term Memory (LSTM) models are capable of predicting stock price trends much better than traditional methods. Although highly effective in stable market conditions, studies also indicate that many forecasting models struggle when market shocks or unusual events occur. Dixon et al. (2020) argue that most current AI-based trading systems still focus on optimizing on historical data rather than developing reasoning capabilities in unprecedented situations.

2.3 The important of Generative AI in financial services

Among the application areas of AI, Wealth Management is considered one of the fields with the strongest potential for transformation. The increase in digital clients, along with the need for access to low-cost investment services, has driven the rapid development of Robo-Advisor platforms (Sironi, 2016). Robo-Advisors use algorithms to assess client profiles, determine risk tolerance levels, and recommend suitable investment portfolios. Research by Waliszewski and Szklarska (2020) shows that these systems significantly reduce advisory costs and expand access to asset management services for individual investors. However, many studies also indicated that current Robo-Advisor systems still have significant limitations. *First*, the investor evaluation process is often based on standardized questionnaires, leading to a simplification of complex human financial behavior (D'Acunto et al., 2019). *Second*, investment recommendations are primarily built on pre-designed optimization rules or models, limiting personalization possibilities. *Third*, the transparency and explainability of the system do not meet user expectations (Jung et al., 2018). These limitations show that although AI has helped automate many activities in asset management, most current systems have not yet reached the level of truly personalized wealth management.

The emergence of Generative AI is creating a significant shift in how AI is applied in the financial industry. Unlike traditional AI systems that focus on forecasting and classification, Generative AI provides the ability to reason, synthesize information, and interact using natural language (Li et al., 2023). Recent studies show that Generative AI can support many financial tasks such as analyzing corporate reports, synthesizing market news, answering investment questions, and assisting in financial planning (Lee et al., 2024). The development of specialized models like FinGPT also shows the potential to build AI systems with in-depth financial knowledge to support investment decision-making (Yang et al., 2023). However, the application of Generative AI in finance still faces many challenges related to reliability, verifiability, hallucination, and regulatory compliance requirements (Li et al., 2023). Therefore, instead of viewing Generative AI as a complete replacement for financial experts, many studies propose a Human-AI Collaboration approach to combine AI reasoning capabilities with human expertise.

It can be seen that AI has brought about significant changes in many financial activities, from credit rating to algorithmic trading and asset management. However, current systems still mainly focus on forecasting and optimization capabilities rather than understanding the individual needs of investors. In particular, in the field of Wealth Management, three main research gaps still exist. First, current Robo-Advisor systems do not support dynamic personalization based on context and changing client needs over time. Second, the explainability and transparency of the investment advisory process are limited. Third, current research has not proposed a framework that simultaneously integrates investor profiles, contextual modeling, generative AI inference, and continuous learning mechanisms within a unified architecture. These gaps highlight the need to develop a new generative AI-based framework to enhance the personalization, explainability, and adaptability of next-generation asset management systems.

3. Proposed framework

To overcome the limitations of traditional Robo-Advisor systems and harness the potential of Generative AI in asset management, this study proposes a Generative AI Framework for Personalized Wealth Management. The framework is designed with a multi-layer architecture, where each layer assumes a distinct role but is closely interconnected within a closed decision-making process. The core objective of the framework is to transform from a rule-based, data-driven investment advisory model to a context-aware, personalized financial advisory system, where Generative AI acts as the central reasoning engine. As illustrated in Figure 1, the framework comprises six main layers: (i) Investor Data Layer, (ii) Investor Profiling Layer, (iii) Context Modeling Layer, (iv) Generative AI Reasoning Engine, (v) Personalized Recommendation Explainability Layer, and (vi) Feedback & Continuous Learning Layer. The overall architecture of the framework is built on a top-down data transformation pipeline model, where raw investor data is gradually transformed through each layer to create investment recommendations that are explanatory and adaptable over time. This approach helps ensure that each investment decision is not only based on financial data but also fully reflects the individual context, behavior, and long-term goals of the investor.

The first layer of the framework is responsible for collecting and standardizing investor data. This data includes demographic information, financial situation, investment experience, risk tolerance, and financial goals. Unlike traditional systems that rely solely on static questionnaires, this layer is designed to support multi-source data integration, including transaction data, user behavior, and external data. The output of this layer is a structured dataset, which serves as the foundation for subsequent analysis steps. *The second layer* is investor profiling, which transforms raw data into meaningful characteristics through behavioral analysis and investor segmentation mechanisms. Specifically, this layer performs four main functions including investor segmentation; behavioral profiling; risk profiling and goal identification. The result of this layer is a dynamic investor profile, reflecting both financial characteristics and investment behavior.

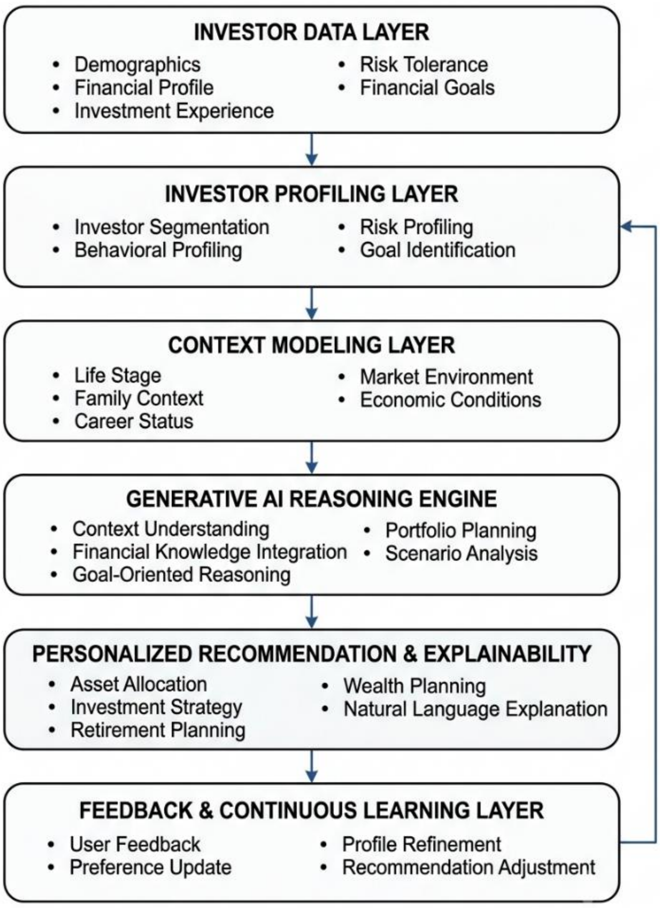

Figure 1. Proposed Generative AI Framework for Personalized Wealth Management

One of the limitations of current Robo-Advisor systems is the lack of ability to consider individual context. To address this issue, the proposed framework adds a context modeling layer to its *third layer*. This layer integrates elements such as life stage; family context; career status; market environment and macroeconomic conditions. Including these elements in the model helps the system shift from static personalization to context-aware personalization. *The fourth layer* is the most important in the framework. This is the central component and plays a core role in the proposed framework. Unlike traditional Machine Learning models that only perform forecasting or classification, the Generative AI Reasoning Engine is capable of understanding complex financial contexts; integrating financial knowledge from multiple sources; performing goal-oriented reasoning; simulating investment scenarios and supporting dynamic portfolio planning. In essence, this layer acts as a financial reasoning system, transforming input information into actionable insights, rather than just providing forecasts. The results from the inference engine are transformed into specific investment recommendations, clearly demonstrated in the *fifth layer*, which includes asset allocation; investment strategy; retirement planning; and wealth planning. A key differentiating factor of this layer is its explainability. The system not only provides recommendations but also offers reasoning in natural language, helping users understand why the recommendation was made; the factors influencing the decision; and the corresponding risk level. This increases user trust and acceptance. *The final layer of the framework* is responsible for continuous learning. User feedback is continuously collected and used to update investment preferences; adjust investor profiles; and optimize the inference model. Improving recommendation quality This loop mechanism ensures that the system is not a static model but an adaptive intelligent system, capable of evolving over time.

In summary, the proposed framework offers three main contributions. *First*, the research proposes a generative AI-driven financial reasoning system architecture, replacing the traditional rule-based approach in robo-advisory. *Second*, the framework integrates three crucial elements simultaneously including investor data, individual context and generative AI reasoning, creating a multi-dimensional personalized model. *Third*, the continuous feedback loop mechanism enables the system to adapt over time, something that current asset management systems have not yet achieved. Unlike previous studies that focused on individual components such as market forecasting or robo-advisory, this framework provides a unified overall architecture in which Generative AI plays a central role throughout the entire asset management value chain. Therefore, the framework is not only practical but also opens up a new research direction on AI-driven personalized financial reasoning systems in the field of asset management.

4. Benefits and challenges -TOE Framework perspective

To evaluate the practical applicability of Generative AI in personalized asset management, this study uses the Technology–Organization–Environment (TOE) theoretical framework. The TOE framework is widely used in technology innovation research to analyze the factors that influence technology adoption and implementation at the organizational level. In the context of the proposed framework, the TOE helps clarify three important aspects: (i) the technological characteristics of Generative AI, (ii) the financial institution's capacity to deploy the system, and (iii) environmental factors such as regulation, market and customer behavior.

4.1. Technology

From a technological perspective, Generative AI offers several significant benefits for asset management. *First*, Generative AI is capable of processing unstructured and multi-source data, including financial reports, market news, and user behavior data. This is superior to traditional models that only handle quantitative data. *Second*, Generative AI provides contextual-aware reasoning, allowing the system to generate investment recommendations tailored to each investor's long-term goals and individual circumstances. *Third*, its natural language generation capabilities significantly improve the interpretability and interaction between the system and the user, thereby increasing transparency and user experience. However, Generative AI also presents several significant technical risks. One of the biggest problems is hallucination, where the model can generate inaccurate financial information that appears plausible. This is particularly dangerous in asset management contexts, where investment decisions require high precision. Additionally, generative AI models often lack reasoning stability, leading to outputs that can change significantly with small changes in input. Finally, the lack of quantitative explainability remains a major limitation, especially when applied in a highly compliant financial environment

4.2. Organization

At the organizational level, Generative AI can create structural changes in the asset management industry. This technology helps reduce the cost of traditional financial advisory services, thereby expanding access to wealth management services for the mass affluent client base. Besides that Generative AI supports financial institutions in automating client advisory and analysis processes, increasing operational efficiency and reducing reliance on human experts. Generative AI-based systems can help build new service models such as hybrid advisory models, combining financial experts and AI. However, the deployment of Generative AI in financial institutions also faces many challenges. A significant issue is the lack of skilled personnel in AI and quantitative finance, leading to a gap between technological capabilities and practical implementation capabilities. Furthermore, integrating generative AI into existing banking and asset management systems is often complex and costly. Another risk is over-reliance on AI, which could diminish the role of financial professionals in decision-making.

4.3. Environment

At the environmental level, the development of Generative AI is driven by several positive factors. The increasing demand for personalized financial services from customers provides a strong impetus for the adoption of AI in wealth management. Simultaneously, the development of the fintech ecosystem and open financial data facilitates the training and deployment of Generative AI models. Many countries are promoting digital transformation in the financial industry, creating a favorable environment for technological innovation. However, the financial environment also presents several significant barriers. One of the biggest challenges is that the legal framework has not kept pace with the development of Generative AI, particularly regarding accountability in automated investment advice. Furthermore, regulations on personal data privacy limit the ability of AI systems to perform deep data mining. Finally, investor confidence in AI in financial decision-making remains low, especially in high-risk investment decisions.

Based on the TOE framework, it can be seen that Generative AI-based Wealth Management offers strong transformative potential for the wealth management industry; however, practical implementation remains limited by three main groups of challenges technical risks related to model reliability, limitations in organizational capacity to integrate AI, and legal barriers and trust from the external environment. Therefore, developing Generative AI systems in wealth management is not only a technological problem, but also an interdisciplinary problem involving organizational and systemic financial risk management.

5. Conclusion

This study proposes a Generative AI framework for personalized asset management, aiming to overcome the limitations of traditional robo-advisor systems that are primarily based on static profile models and portfolio optimization according to fixed rules. Unlike previous approaches, this research builds a multi-layered architecture integrating investor data, contextual modeling, and the reasoning capabilities of Generative AI within a closed decision-making system. The proposed framework comprises six functional layers, and this combination allows the system to transition from a static financial advisory model to a contextually and temporally adaptive financial advisory model.

This research contributes to the literature in three important ways. First, it expands the role of artificial intelligence in finance from predictive models to generative reasoning systems. This changes the traditional approach to asset management, which is primarily based on portfolio optimization using historical data. Secondly, the study proposes an integrated, multi-layered system architecture where investor data elements, individual context, and Generative AI inference mechanisms are connected within a unified structure. This approach overcomes the fragmentation found in previous studies, which often focused on individual components such as robo-advisory, explainability, or portfolio optimization. Thirdly, the study utilizes the Technology–Organization–Environment (TOE) framework to explain the application of Generative AI in asset management, thereby providing a systemic perspective on the interaction between technological capabilities, organizational capacity, and the institutional environment in the financial industry.

From a practical perspective, this study offers a reference architecture for the design and implementation of next-generation AI-enabled wealth management systems. *For financial institutions*, the proposed framework provides a structured approach to developing investment advisory solutions that support deep personalization, dynamic adaptation to evolving investor circumstances, and greater transparency in recommendation generation. *For fintech firms*, the framework highlights the strategic value of integrating large language models (LLMs) with domain-specific financial reasoning capabilities, thereby extending the role of Generative AI beyond content generation toward intelligent financial decision support. Furthermore, the framework provides *policymakers and regulators* with a conceptual basis for addressing emerging governance challenges associated with AI deployment in financial services, particularly those related to transparency, accountability, explainability, and system reliability. Collectively, these implications contribute to the responsible development and adoption of Generative AI in wealth management ecosystems.

Despite its contributions, the study has some limitations that need to be considered. The study is conceptual and has not been validated with empirical data; therefore, it is not possible to quantitatively assess the effectiveness of the proposed framework under real-world market conditions. At the same time, the technical details of the Generative AI model have not yet been explored in depth, including the specific model architecture, training mechanisms, or optimization methods in the financial environment. Investor behavior factors are integrated at the overall structural level but have not been modeled in detail according to behavioral finance theories, thus limiting the extent to which they explain decision making behavior.

Building upon these limitations, several promising avenues for future research emerge. First, empirical validation is needed to assess the effectiveness of the proposed Generative AI framework in real-world wealth management settings. Future studies may compare GenAI-driven advisory systems with conventional robo-advisors across multiple dimensions, including portfolio outcomes, investor satisfaction, trust, engagement, and behavioral responses. Second, further research should develop robust evaluation frameworks and quantitative metrics tailored to AI enabled financial advisory systems, particularly with respect to reasoning consistency, explainability, recommendation quality, reliability, and user acceptance. Third, greater attention should be devoted to investigating human AI collaboration in investment decision making, with the aim of identifying effective task allocation mechanisms and governance structures that leverage the complementary strengths of human expertise and AI capabilities. Finally, interdisciplinary research integrating artificial intelligence, quantitative finance, behavioral finance, and information systems is essential for advancing the theoretical foundations and practical implementation of next-generation intelligent wealth management systems. Such efforts will contribute to the development of more adaptive, transparent, and human-centered financial advisory services.

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