

FROM RIGID ROBO-ADVISORS TO HUMAN-LIKE INTERACTIONS: REVOLUTIONIZING FINANCIAL ASSISTANCE WITH LLM-POWERED SOLUTIONS

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ABSTRACT

Generative Artificial Intelligence (GenAI) is revolutionizing the business world by increasing availability, efficiency, cost reduction, and innovation. This paper explores the application of Large Language Models (LLMs) and GenAI to finance. It proposes a novel framework on how we can imagine robo-advisory systems, from a traditional rigid platform to a more humanized solution that further engages the investor in a hand-picking asset selection process and better understands their goals and profile using LLMs. We designed an end-to-end solution to overcome many limitations such as lack of flexibility in robo-advisors, lack of possible asset types (usually only equities) and the problem of real-time access to high quality data. The solution architecture includes dynamic client profiling, risk aversion estimation and portfolio optimization. Using robust data pipelines to curate the latest market information, the Asset Selector Agent has been customized. Through iterative development, we employed prompt engineering and multi-agent workflows to enhance user interactions and deliver meaningful insights. By developing an innovative chatbot platform, we demonstrate the potential of LLMs to transform customer service, increase engagement, and provide strategic financial advice.

KEYWORDS

Generative AI, Large Language Models (LLMs), Big Data, Practical Applications, Agentic Design Patterns, Finance, Investment analysis, Portfolio Optimization

1. INTRODUCTION

Financial chatbots hold immense potential to revolutionize the banking landscape. By harnessing the capabilities of Large Language Models (LLMs), financial institutions can unlock new avenues for innovation and customer engagement. The advanced natural language generation provided by LLMs enables chatbots to make hyper-personalized recommendations, anticipate customer needs, and facilitate more nuanced conversations, allowing people to think outside the box and unleash their creative potential to solve more problems and increase the return on investment (ROI) of chatbots. Banks gain a strategic advantage by utilizing AI chatbots, powered by LLMs, to meet evolving customer preferences and competitive market demands. In addition to streamlining routine transactions, these chatbots enable banks to

provide customized financial advice, predictive analytics, and seamless integration with other banking services. In addition, by prioritizing a customer-centric approach, banks can foster deeper connections with customers, building long-term loyalty and trust. As the banking industry continues to embrace digital transformation, the potential applications of financial chatbots with LLM are limitless presenting an exciting opportunity for banks to innovate and differentiate themselves in a rapidly changing market [1, 2, 3].

In the quest for more efficient and dynamic conversational interfaces, there is an urgent need to explore the potential of Generative Artificial Intelligence (GenAI), particularly in the area of text generation. Traditionally, manual design of conversational flows has been the norm, but with the advent of GenAI models, such as those recently added to Copilot Studio (formerly Microsoft PVA), there is an opportunity to completely rethink this process [4]. As a result, financial institutions, such as banks, have begun to explore the power of GenAI to solve their business use cases and work on solutions that align with their strategies and needs, such as revolutionizing the robo-advisor to provide more flexibility to their customers [5].

In this work, we took a hypothetical customer scenario of a real bank, as it is our clients. And we explored the opportunities offered by Copilot Studio, one of the powerful solutions offered by the Microsoft Power Platform. We have shifted our focus to how LLMs can evolve financial advisory applications from rigid robo-advisors to more interactive, flexible and customized solutions that meet the growing expectations of clients, while balancing asset performance and suitability with clients preferences and profile. Using prompt engineering techniques, we designed a real-time, robust, and scalable data collection and curation pipeline that allows our application to access the latest market data in a high-quality format (we can see the technical implementations in <https://github.com/Andolsi-Hamza05/financial-advisor>). We then created a machine learning (ML) model to estimate the client's risk profile. We streamlined the customer profiling process with agentic workflow to ensure that we take the investor's profile into account in our interactive asset selection. After identifying the best potential performing assets that match the client's profile, we feed the data into our portfolio optimization engine.

2. BACKGROUND

In 2017, Google introduced the Transformer architecture [10], marking a significant advancement in natural language processing. Transformers represent each word as a token and create an attention map that illustrates the relationships between these tokens. This contextual awareness enhances the model's ability to generate coherent text, as demonstrated by large language models. Unlike discriminative models that focus on classification, generative AI models create new content by learning patterns and relationships from datasets generated by humans [6]. Generative AI is transforming various fields, with foundational models leading the charge. Models like ChatGPT exhibit impressive multitasking abilities, seamlessly performing tasks such as summarization, question answering, and classification [11]. Their versatility allows for easy integration into specific applications with minimal training and example data requirements.

Complementing this innovation is MFTcoder, an advanced multi-task fine-tuning framework designed specifically for code LLMs. By enabling simultaneous fine-tuning across multiple tasks, MFTcoder effectively addresses common challenges in model training, resulting in enhanced performance and efficiency compared to traditional methods. Seamlessly integrated with popular LLMs such as CodeLLama and Qwen, MFTcoder establishes a new benchmark in code generation, outperforming GPT-4 on benchmarks like HumaneEval [12, 13, 14].

2.1. Problematic

A financial advisor is typically someone who guides investment clients to provide them with insightful metrics, help them clearly identify their goals and set realistic expectations, and make recommendations on where to invest their money. This work requires a strong knowledge of financial markets, financial engineering skills, mathematics and statistics, AI and big data skills. Since the market is very volatile and always changing, automating this process is like a myth and can lead to losing money if AI is not used properly.

We focused on exploring LLM in prototyping a financial advisor application that helps investors build their portfolios based on their preferences, market trends, and asset analysis. First, the AI agent interacts with customers to perform customer profiling and understand their preferences. It sends data to the machine learning model used to get an estimate of the risk aversion (tolerance) coefficient. Then, based on natural language prompts, it selects investments from the investment data available in the database. In the context of a banking customer service chatbot, we may need to implement a custom RAG if:

- We require integration with our bank's proprietary systems or databases to retrieve customer information or perform transactions.
- We seek domain-specific knowledge or expertise to handle complex banking-related queries or tasks.
- We have to reach high accuracy or performance metrics for specific banking-related tasks, such as validating fraud detection before processing a transaction.

In this case, we have created a tailored and accurate conversation experience for bank customers.

2.2. Customer Profiling

The client profiling part is essential for every new investor customer meeting with the financial advisor. In this first meeting, the financial advisor tries to understand the client's profile, savings, budget, assets already held, and many other relevant information that can give a better estimate of risk profile (for this part we used a machine learning model to assess the client's risk profile). Next, the financial advisor helps the investor clarify the main goal and make sure it is SMART (asks about any preferences the client would like the financial advisor to consider).

Defining a SMART goal is critical to setting realistic expectations, measuring the success of the portfolio, and intelligently selecting the assets that match the client's preferences, profile, and goal. To ensure the goal is SMART, we first present our proposed agentic workflow for guiding the investor client to define a clear and SMART goal.

(S) The goal should be **Specific**: The investor should clearly define the goal in a specific way. For example, planning for retirement, for children's education, for buying a car, etc. We prompted the LLM to extract the goal and based on that decide whether the goal is specific or not.

(M) The goal should be **Measurable**: By measurable, we mean first, a well-defined quantitative target (I want to have 500 000\$ for my retirement, The car costs 1 700 000\$, etc.). Second, the amount of money to be invested, this can be an initial investment (I am willing to invest 8000 \$ initially..) or a monthly/annual investment (or contribution) like I am able to contribute 500\$ monthly to my investments. The investor

must define the target value and should clearly define at least one of the following: initial investment and monthly/annual contribution. We can accept both (the investor can invest with initial investment and/or monthly/annual contribution). The LLM should extract these values and decide whether the goal is measurable or not based on the presence of the specified values with if/else statements.

(T) The goal should be **Time bound**. This means that the investor should set a clear time frame (time horizon) for his investment goal. The time after that he should achieve his specific goal. Therefore, the LLM should clearly outline the time frame, if specified, and adjust the is-time value accordingly to either True/False.

(A) The goal should be **Achievable**! For example, the investor cannot invest 1000\$ and expect to have a fortune of 1 000 000\$ in a year. For this example, the goal is considered as not achievable.

For this task, we considered that the (R) which stands for **Relevant** in SMART is verified since we assume that the investor is clarifying a goal that aligns with his ambitions. But how can we decide if the future value of the investment meets the goal value? One of the limitations of LLMs is their mathematical reasoning abilities. LLMs are prone to errors when it comes to extracting complex financial values and independently calculating the results. We addressed this limitation by creating a ReAct framework [15] unit equipped with a pythonic function that acts like a calculator used by the LLM with a tool calling (Langchain is often used with ReAct framework where the LLM thinks and decides if the tool can help in solving the task or not).

3. DATA AND METHODS

In order to keep our database up-to-date and represent the actual market state and asset related information, we designed a near real world pipeline: Data collection microservice that collects real-time data from financial data sources. We ensure that only new data is processed by the feature selection engine. We compute some important metrics, do some data validation checks to get the final gold layer [16]. Finally, the selected assets and the relevant information of the investor such as risk aversion coefficient are sent to the portfolio optimization microservice. This microservice provides an optimal portfolio and writes a detailed report explaining the choices and some useful visualizations via a friendly user interface.

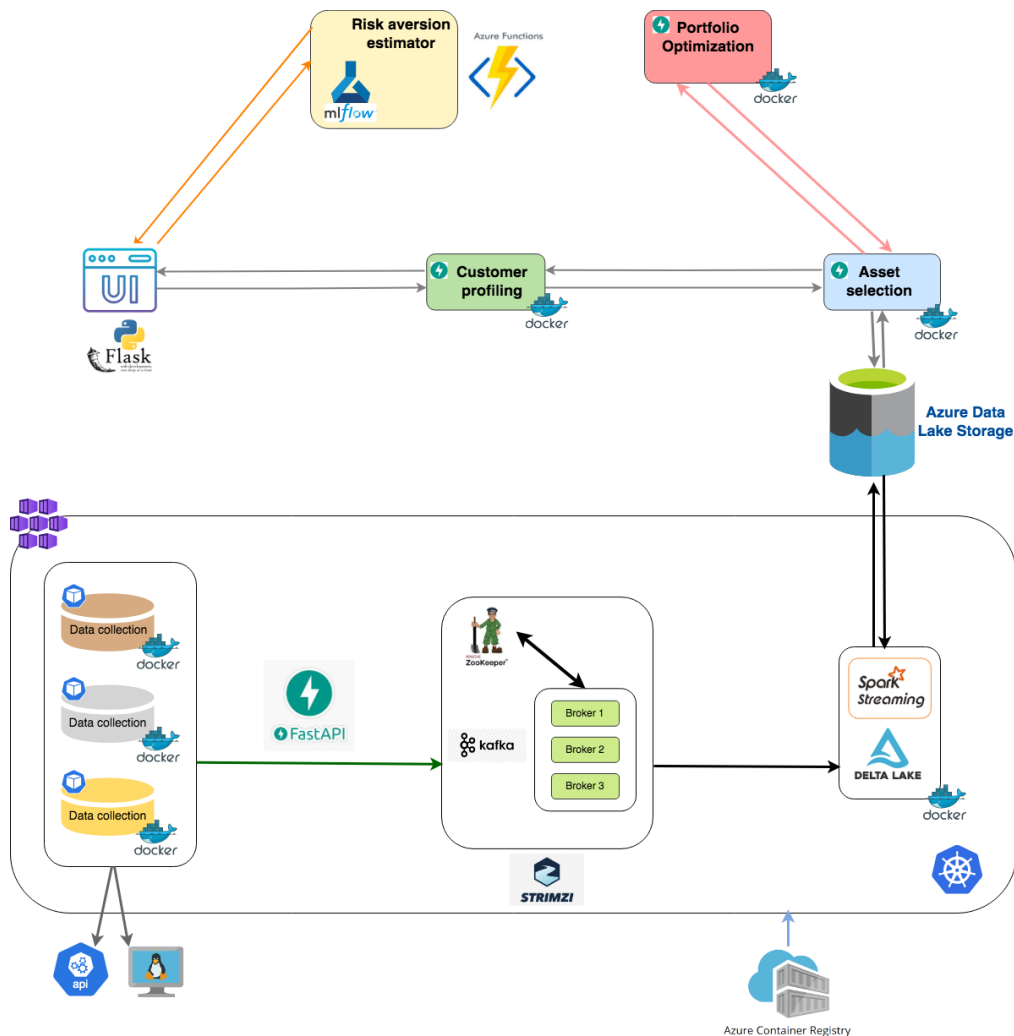


Figure 1: Financial advisor workflow of our proposed solution

Designing the architecture for this solution requires a deep understanding of the workflows of quantitative development and financial engineering, as well as expertise in asset portfolio optimization. It also requires a strong understanding of big data technologies, software development, system design, networking, and cloud engineering. To ensure that asset data accurately reflects real-time market dynamics, the system includes a near real-time data pipeline. The data collection microservice is tasked with collecting information from diverse financial sources through more than 20 exposed endpoints that are activated by scheduled cron jobs every five minutes. This microservice scrapes real-time market data and passes it to Kafka - our message broker - with each data point routed to its corresponding topic. A high-level system architecture diagram, as shown in Figure 1, includes several microservices, including customer profiling, data collection, the Kafka message broker, data preparation, risk assessment, portfolio optimization, and asset selection.

3.1. Data

The proposed approach involves scraping financial data from Yahoo Finance and using state-of-the-art LLMs, including OpenAI's models and BloombergGPT, within a RAG framework. The data is pre-processed and analyzed to identify key financial indicators. Different LLMs are

compared to determine the most effective model for generating investment scenarios. Optimization techniques are then applied to refine scenarios for different investor profiles, balancing potential ROI with risk. The nature of financial data is complex, influenced by a wide range of factors such as market sentiment, economic indicators, geopolitical events, and more. Building a unified pipeline that captures all of these nuances can be daunting. Indeed, the industry typically has teams focused on narrow areas, like a specific market, asset class or industry, like finance or health. To address the multiple challenges of financial data (volume, velocity, variety, data quality and integrity, etc.), we implemented a structured, tiered approach that follows the **Medallion Architecture**. It leverages a tiered data transformation process that moves from raw data (Bronze layer) to refined, enriched data (Silver layer) and finally to fully optimized and analytics-ready data (Gold layer).

3.1.1. Bronze Layer: Raw Data Ingestion and Storage

The bronze layer acts as the foundational layer of the architecture, where raw, unfiltered data is ingested and stored. At this stage, there is no cleaning or processing of the data, and the data is preserved in its original schema and format. This layer is critical for auditability, allowing us to trace any analysis back to the original data source. In our case, data is ingested via Kafka streams. Raw data can include price tickers, economic indicators, or market news articles.

At this stage, the data is stored in Azure Data Lake Storage (ADLS), which provides scalable, secure storage for large volumes of raw data. Partitioning is critical here, typically by asset type, to enable efficient retrieval and parallel processing of data.

3.1.2. Silver Layer: Data Cleansing and Enrichment

The silver layer is where the raw data is refined, cleaned, and enriched. This stage focuses on removing outliers, filling in missing data, and transforming the data into a more consistent and usable format. For example, corporate action events such as stock splits or dividend payments must be taken into account to avoid distorting historical pricing data.

Common transformations include:

- **Data Validation:** Financial data are sometimes inaccurate. We perform checks to remove any erroneous trades (e.g., price anomalies or bad ticks) using pre-defined rules based on market conditions.
- **Normalization:** This stage involves standardizing data from different sources and formats. For instance, currency conversions may be applied to normalize asset prices, or time zones may be aligned across global data feeds.
- **Feature Engineering:** Enrichment processes include the creation of technical indicators (e.g., moving averages, RSI), the calculation of financial ratios (e.g., P/E ratio), or even sentiment analysis based on news data. These features are critical inputs to risk models or trading algorithms.

3.1.3. Gold Layer: Analytics and Aggregation

The gold layer is the final stage where the refined data is aggregated, optimized, and made ready for high-value analytics, reporting, and machine learning models. At this level, the data is structured for our asset selector microservice, ready to be interacted with by LLM.

3.2. Asset selection

Once the client profiling phase has been successfully completed and the investor has confirmed their final preferences, the asset selector takes all the relevant profile information and natural language preferences and incorporates them into the asset selection process. We start with the manager agent. This is the one that distributes the tasks to each sub-manager or (asset level manager), see Figure 2. Here the asset manager decides on an execution plan based on the template provided by the Manager, taking into account the other agents. For the Stocks manager, we have introduced a more complex workflow that allows agents to interact with the stock search agent tool. First, the stock manager divides the preferences into CSV agent Stocks CSV manager tasks and Stocks searcher tasks. The stock manager can decide if the preference can be checked from the available dataset in the gold layer (this is done by passing the schema of the dataset in the prompt so that the agent know what features are available in the dataset), else these preferences should be verified through web-search tools.

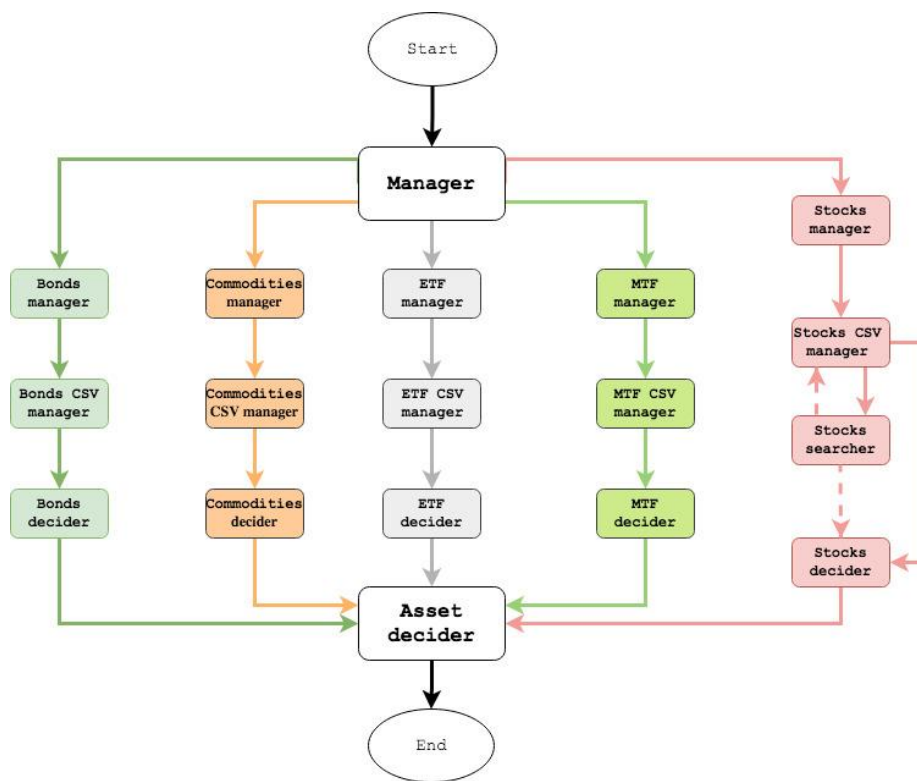


Figure 2: Asset selector agentic workflow

Manager Agent. The asset selection workflow takes as input the asset allocation proportions for each asset type, the preferences, and the risk aversion coefficient. First, the manager agent Manager checks if the preferences have some company granular level requirements, then it will reduce the mutual funds (MTFs) and ETFs proportions to 0. In other words the Manager won't route the assets to their respective asset managers.

Asset Manager Agent. This manager uses the ReAct framework, plans and decides which tools it is going to use to pick assets with the given constraints. For instance, for the Stocks manager:

- The number of stocks to be selected should correspond to the investor's risk level (for example, if the client has an aggressive profile, he may be interested in small-cap companies, i.e. companies with a market capitalization of less than 300 million \$).
- Parse preferences and decide whether to check them using search tools from external sources (basically the Internet) or using the internal data source (the gold layer obtained from the data curation pipeline).

3.3. Portfolio Optimization

Portfolio optimization involves selecting the optimal portfolio — a collection of assets — that maximizes expected returns for a specified level of risk, or minimizes risk for a given expected return. Various methodologies can be employed to achieve this objective, including Mean-Variance Optimization, the Treynor-Black Model, and the Black-Litterman Model [17].

Developed by Harry Markowitz in the 1950s, Mean-Variance Optimization is a fundamental approach to portfolio construction [18]. It aims to create a portfolio that minimizes variance (risk) for a given expected return, or maximizes expected return for a given level of risk. The Treynor-Black Model integrates active management with a passive portfolio approach. It provides a framework for combining the results of an active manager with a market portfolio. The model starts with two components: an active portfolio and a market portfolio. The Black-Litterman Model extends the Mean-Variance Optimization by incorporating subjective views into the asset return expectations. This model allows investors to adjust expected returns based on their beliefs while maintaining the equilibrium provided by the Capital Asset Pricing Model (CAPM).

The Black-Litterman model offers a flexible approach to portfolio optimization by combining market equilibrium with the investor's insights, resulting in a stable and reliable portfolio weights. Additionally, advanced clustering techniques [19] improve portfolio diversification, while Monte Carlo simulations allow for testing portfolio performance under various future scenarios. This approach opens up the possibility of developing trading algorithms, moving beyond a sole focus on asset allocation.

4. RESULTS

Building a robust financial data pipeline is both a technical and conceptual challenge. In the real world, unforeseen issues often arise, such as sudden regulatory changes that require modifications to the pipeline, or data vendor outages that disrupt the flow of critical market data. One of the most challenging issues is ensuring data consistency across asset classes and time zones, especially when dealing with global markets. Even a small mismatch in timestamps or missing corporate actions can lead to incorrect portfolio calculations and ultimately poor investment decisions.

By leveraging the Medallion architecture, we mitigate many of these challenges by isolating raw data, applying transformations, and producing analytically-ready data sets in a structured, auditable manner. This architecture not only provides scalability and flexibility, but also ensures the accuracy and reliability of the data consumed by financial models and reports.

The dataset encompasses 19 countries: France, Germany, Italy, Austria, China, the UK, India, Australia, Brazil, Canada, Japan, South Korea, Malaysia, the Netherlands, Sweden, Egypt, Qatar, Saudi Arabia, and South Africa. It places special emphasis on the US stock market while

also including a diverse range of assets from various regions worldwide. This global representation is a key strength of our data, as it is essential for mitigating systemic risk by ensuring a comprehensive array of financial assets across different markets [20].

We also covered different types of financial instruments. This is not an exhaustive dataset for all types of financial assets - for example, we do not directly include cryptocurrencies here, although there are some mutual funds (MTFs) that create a portfolio of digital assets - but the idea is to deal with different types of assets as much as possible and try to mix and choose the best combination with different metrics for each asset to meet the needs and specific requirements of the investor. Each dataset contains multiple attributes that capture both raw and derived metrics relevant to financial markets.

The descriptions of the tickers used in the portfolio are as follows: Amazon (AMZN), are leaders in their respective sectors and offer a wide range of services and products; Bank of America (BAC) is a major financial institution, while Costco (COST) is known for its membership-based warehouse clubs. The Walt Disney Company (DIS) is a global entertainment giant with interests in film, television and theme parks. Domino's Pizza (DPZ) is known for its chain of pizza restaurants and delivery services. Coca-Cola (KO) dominates the beverage market with its iconic soft drink. McDonald's (MCD) is a major player in the global fast food industry. In the technology sector, Microsoft (MSFT) excels with its software and hardware solutions. Nordic American Tankers (NAT) specializes in the maritime transport of crude oil, while Starbucks (SBUX) is an international coffee house chain celebrated for its premium coffee products. These companies exemplify the diversity and innovation of today's business landscape. We evaluated various portfolio optimization techniques. In Table 1 we can find the allocated weights to each portfolio optimization model: We can notice that the KO ticker for instance in Black-Litterman model has 0 as a weight. The Treynor-Black has a weight equal to 0.11, which is the third most important weight given by this method.

However, the DPZ ticker has a weight larger than 0.1 for all of the three models. This can be a good indicator of the importance of this asset given the profile of the customer (because we do not take into account only the metrics and the performance of the asset, we include some customer related constraints like his risk aversion coefficient).

Table 1. Weights of a portfolio: Black-Litterman, Mean-Variance, and Treynor-Black

Ticker	Black-Litterman	Mean-Variance	Treynor-Black
BAC	0.15031	0.02390	0.006048
COST	0.05212	0.16444	0.020219
DIS	0.05504	0.03166	0.047210
DPZ	0.15471	0.22786	0.151021
KO	0.00000	0.05204	0.119128
MCD	0.09987	0.09086	0.086184
MSFT	0.13623	0.14015	0.077446
NAT	0.11765	0.00000	0.206404
SBUX	0.09270	0.10472	0.052783
AMZN	0.14138	0.16438	0.019488

5. DISCUSSION AND CHALLENGES

The financial industry continues to look for ways to innovate and improve investment decisions. The integration of RAG and LLM offers a promising approach to analyze large amounts of

financial data and generate tailored investment scenarios. The aim of this study is to use these advanced techniques to improve the formulation of investment strategies and provide clear insights into the return on investment (ROI) and risk for different investor profiles.

The findings of our study underscore the critical role of accurately estimating the risk aversion coefficient in financial advisory and asset allocation. By leveraging machine learning techniques, financial advisors can obtain a more nuanced understanding of individual client preferences, leading to tailored investment strategies that align with each client's risk profile. Our approach is a solution when time matters and we need real time inference of the model, by incorporating a broader range of predictive variables and allowing for the dynamic modeling of risk aversion. This not only enhances the reliability of risk assessments but also empowers financial advisors to make informed decisions that can significantly impact their clients' investment outcomes in an agile way.

Future research should explore the integration of behavioral finance principles, market news sentiment and economic indicators into machine learning models to further enhance the accuracy of risk aversion predictions (available data is always a limitation to start exploring these avenues). In addition, the incorporation of real-time market data could provide a more comprehensive framework for assessing investor risk tolerance in an ever-evolving financial landscape. Data bias refers to the presence of biases and imbalances in the training data that lead to skewed model outputs. Limited world knowledge and hallucination occur when language models lack a comprehensive understanding of real world events and tend to fabricate information. In general, the performance of language models is highly dependent on the quality and representativeness of the training data. Ethical concerns revolve around the responsible and ethical use of language models, especially in sensitive contexts. The issue of bias amplification is prominent, as biases present in the training data may be exacerbated, leading to unfair or discriminatory results. There are potential legal and copyright issues related to generated content that may infringe on copyrights or violate laws. User privacy is a key concern here, particularly the risks of generating text from user input which might contain confidential or sensitive information. Computational resources are a major concern due to the significant computational power required. There are interpretability challenges in understanding and explaining the decision process of complex models. Evaluating models across tasks and domains is poorly designed, adding further complications. In addition, there are fine-tuning challenges in adapting pretrained models to specific tasks or domains. Maintaining coherent contextual understanding over longer passages or conversations is another difficulty. Language models are also vulnerable to adversarial attacks, where deliberate manipulation of input data can lead to incorrect outputs [21]. Finally, maintaining long-term context and coherence over extended text or conversations is an ongoing struggle.

There are several key issues to consider when deploying language models in production environments. First, scalability is critical to ensure that the model can efficiently handle increased workloads and demand. Latency must be minimized to ensure fast and efficient interactions. Robust monitoring and maintenance systems must be implemented to track model performance and perform regular maintenance. Smooth integration with existing systems such as software, databases, and infrastructure is essential. Cost management strategies are important to optimize the costs associated with deploying and maintaining large language models. Addressing security concerns by mitigating potential vulnerabilities and risks is critical. Ensuring interoperability with other tools, frameworks, or systems is another important consideration.

Developing mechanisms to incorporate user feedback for continuous improvement is important to the effectiveness of the model. Adherence to regulatory compliance requirements and standards is mandatory.

Finally, effectively managing the generation of text in dynamic content-handling environments is also an important consideration. Corrective RAG [22] and RAPTOR [23] are some of the very different proposed solutions to adapt RAG frameworks. For the asset selection process, we could potentially use Variational Auto-encoders (VAE) [24]. Another direction in this study could potentially benefit from real-time data signals, using advanced time series analysis or using Kalman filters to extract powerful insights from market fluctuations [25].

6. CONCLUSION

We designed a near real-time data collection pipeline, refined the large amounts of data collected, considering the importance of time in leveraging insights with current data. We improved the process of completing questionnaires and conducting face-to-face meetings to clearly define risk aversion, client profile and understand investor preferences, which a financial advisor used to do manually. In addition, we tested another agent-based workflow that is able to select investments based on the client's natural language preferences, giving the customer full control over the selection of assets. This manual selection process is always a challenge for investors with values, ethical and environmental concerns.

This work can be further enhanced by using the latest RAG solutions, Agentic RAG, Agentic Chunking, to further refine our LLM used for generation on financial and banking corpus and give it a more customized persona. This solution has the potential to significantly impact the future of finance by addressing concerns around scalability, privacy and customer trust. It could reshape the way customers interact with financial services by offering a more engaging, dynamic and responsive alternative to traditional robo-advisors.

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