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Research on Generative Artificial Intelligence for Virtual Financial Robo-Advisor

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Abstract: This research explores the intersection of artificial intelligence and finance, focusing on the emergence of intelligent investment advisers, commonly known as Robo-advisers (RAs). These RAs utilize robust computer models and artificial intelligence algorithms to deliver personalized asset management investment plans for users. Notably, Wealthfront is highlighted as a prominent platform in this field, offering automated investment management services aimed at optimizing investment returns. The study investigates the impact of users' past investment performance on their adoption of intelligent advisers, considering factors such as previous defaults and recent investment performance. It reveals that frequent adjustments to the use of intelligent advisers may hinder long-term investment objectives, emphasizing the importance of consistent usage to fully capitalize on their benefits. Furthermore, the research emphasizes the significance of transparency, user-friendly interaction design, and tailored financial services to foster user trust and enhance the optimization of intelligent advisers' design.

Keywords: Artificial Intelligence (AI); Robo-advisers (RAs); Wealthfront; Investment Performance.

1. Introduction

Artificial Intelligence (AI) endeavors to enhance machine intelligence, often measured by the ability to engage in conversations with humans undetectably, typically via teletype equipment. Traditional investment advisers traditionally operate from the perspective of investors, assisting them in managing their portfolios according to their risk preferences and adapting to market dynamics. However, these tasks historically required labor-intensive and costly manual efforts, inadvertently erecting barriers to entry that favored high net worth individuals.

The advent of robo-advisers revolutionizes portfolio management by significantly reducing human intervention. Now, asset management can be executed seamlessly by a network of computers, democratizing access to wealth management services beyond the affluent clientele. [1]Leveraging powerful computer models and AI algorithms, intelligent investment advisers, exemplified by platforms like Wealthfront, analyze vast customer datasets to craft personalized asset management strategies tailored to individual risk profiles and investment objectives.

Wealthfront, as a leading intelligent advisory platform, harnesses machine learning and quantitative techniques to furnish clients with bespoke asset portfolio recommendations. These recommendations encompass diverse asset classes, including stocks, options, bonds, and real estate, all aimed at optimizing investment returns through automated management services.

The influence of a user's past investment performance on their adoption of smart advisers can be understood through two potential mechanisms. [2]Firstly, users who have experienced subpar performance in manual trading may be more inclined to seek the assistance of intelligent advisers to enhance their investment outcomes, thereby increasing the likelihood of adopting such services. Conversely, poor performance may also signify a history of defaults, engendering heightened risk perception among investors and potentially deterring them from embracing new technologies.

While these mechanisms may counterbalance each other's effects, the prevailing question addressed in this study pertains to which mechanism holds greater sway in the context of P2P online lending. This inquiry underscores the nuanced interplay between past performance, risk perception, and the adoption of innovative financial technologies.

2. Related Work

2.1. The Fusion of Artificial Intelligence and Finance

Industrial intelligence is the mechanism behind intelligence, particularly the software that drives artificial intelligence. Artificial intelligence has the capacity to simulate human thought processes and engage in intelligent decision-making akin to humans. It delves into the cognitive, learning, and operational mechanisms of the human brain, with research findings serving as the bedrock for the advancement of intelligent software and systems. Intelligent finance is predominantly propelled by core artificial intelligence technologies such as machine learning, information processing, knowledge mapping, and computer vision[3]. These technologies empower all stakeholders within the financial industry, augmenting business capabilities and emphasizing the pivotal role of product innovation, process optimization, and service enhancement.

The ecosystem of intelligent finance encompasses regulatory management systems crucial for traditional financial institutions, emerging financial entities, and companies providing artificial intelligence services to financial institutions. [4]Together, these entities form a dynamic intelligent financial ecosystem.

In the era of "it+ Finance" 1.0, spanning the late 1990s, computers and information technology began to permeate daily operations and financial transactions of financial institutions. This era witnessed the advent of electronic accounting for deposit, remittance, and loan transactions, alongside advancements in infrastructure such as magnetic stripe credit card technology, ATMs, and POS machines, significantly enhancing data processing capabilities and financial service efficiency. In the subsequent stage of Internet + finance, internet technology expanded the horizons of financial transactions, while big data and cloud computing bolstered business efficiency. Services like online banking, mobile banking, cardless payments, internet-based credit facilities, and personal finance services emerged, catalyzing the convergence of finance and technology.

Application Models and Case Studies of Artificial Intelligence in Finance:

1. Enhanced Decision-Making with Smart Advisors:

Smart advisors, empowered by big data, cloud computing, and artificial intelligence, are transforming traditional financial investment advisory services. In addition to providing informational consultations, these advisors excel in asset management and allocation, functioning as automated fund managers capable of making data-driven decisions to optimize investment strategies and maximize returns.

Therefore, from the application point of view of generative artificial intelligence, the preparation for creating generative artificial intelligence is relatively adequate in terms of technology and strategy, and the preparation degree in terms of risk and talent is much lower. The risk prevention and related talent reserve of generative artificial intelligence will be the focus and difficulty.

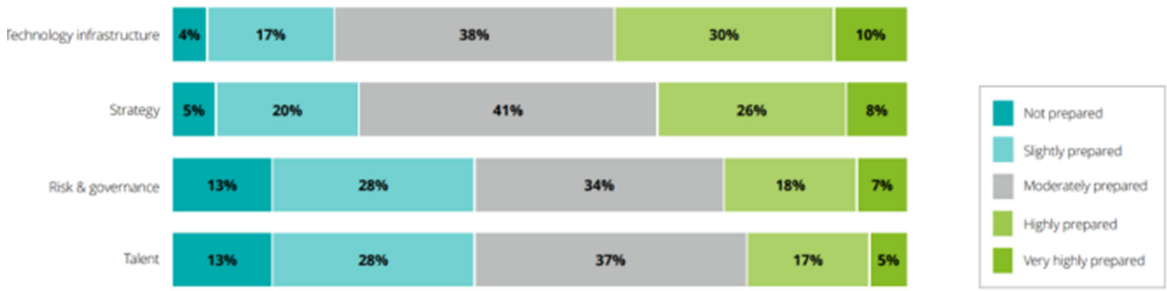

Figure 1. Current readiness for generative AI

2. Case Study: The Rise of Intelligent Investment Advisory:

The integration of big data and artificial intelligence has propelled the emergence of intelligent investment advisors as a cornerstone of the contemporary financial market[5]. Despite their recent introduction to the Chinese market, these smart advisors have swiftly gained prominence, reshaping investment practices and strategies. Leveraging advanced technologies, including AI-powered algorithms, these advisors conduct comprehensive investment research, qualitative analysis, and quantitative modeling, underscoring the importance of robust technical infrastructure to support their operations and ensure optimal performance.

3.Algorithmic Trading

Artificial intelligence is increasingly utilized in algorithmic trading strategies, where complex algorithms analyze market data in real-time to execute trades automatically. These algorithms leverage machine learning techniques to identify patterns, trends, and anomalies in financial markets, enabling rapid and precise decision-making. Case studies have shown significant improvements in trading efficiency and profitability through the integration of AI-powered algorithmic trading systems.

The generative model is constructed using a variety of neural network architectures, the core of which is to define the organization of the model and the flow path of information in the model. Among them, variational autoencoders (VAE), generative adversarial networks (GAN) and Transformer are the most well-known architectures. Google's Transformer architecture, first demonstrated in a groundbreaking paper published in 2017, provides powerful power for today's large language models. However, for other types of generative AI such as images and audio, the Transformer architecture is not the best choice.

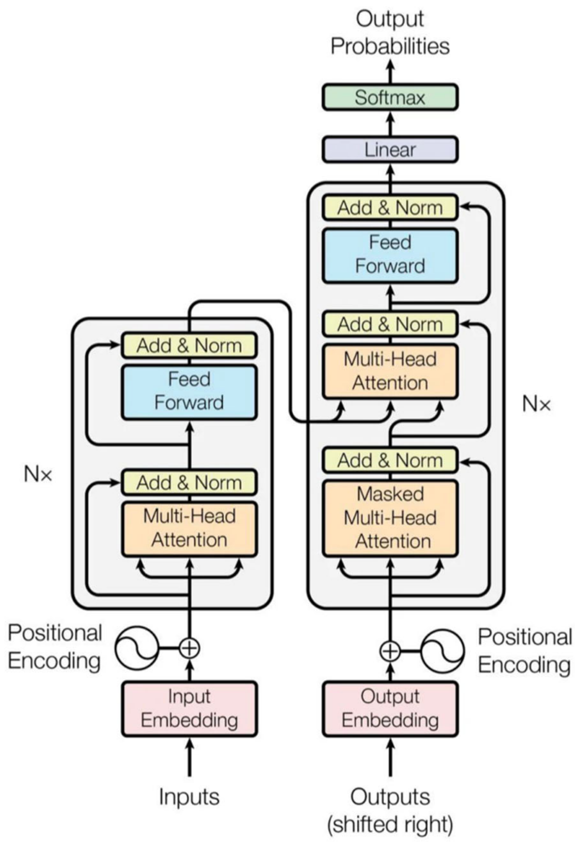

Figure 2. Generate the model Transformer architecture

Autoencoders learn efficient representations of data through the encoder-decoder framework. The encoder compresses the input data into a low-dimensional space, the underlying (or embedded) space, preserving the most essential features of the data. The decoder then uses this compressed representation to reconstruct the original data. Once the autoencoder has been trained in this way, it can use the novel input to generate a suitable output. These models are often used in image generation tools and play an important role in the field of drug discovery, enabling the generation of new molecules with desired properties. As a result, Transformer is a leader in generative AI architecture, and it is at the heart of today's powerful Large Language models (LLMS). Its advantage lies in its unique attention mechanism, which enables the model to focus on different parts of the input sequence when making predictions. In language model applications where input is made up of sequences of words that make up sentences, Transformer is able to predict what words might come next

4.Risk Management

Artificial intelligence plays a crucial role in enhancing risk management practices within the financial sector. AI-powered risk management systems utilize advanced analytics and predictive modeling to assess and mitigate various types of financial risks, including credit risk, market risk, and operational risk. By analyzing vast datasets and identifying potential risk factors, these systems enable financial institutions to make informed decisions and safeguard against potential losses. [6]Case studies have demonstrated the effectiveness of AI-driven risk management solutions in improving risk assessment accuracy and optimizing risk mitigation strategies.

By incorporating these additional application models and case studies, we can further illustrate the diverse applications of artificial intelligence in finance, spanning from investment advisory services to algorithmic trading and risk management. These examples underscore the transformative impact of AI on the financial industry, driving innovation, efficiency, and risk mitigation strategies to new heights.

2.2. Evolution of Traditional Financial Advisory Services

Traditional financial advisory services encompass face-to-face or remote consultations provided by seasoned financial advisers or experts, aimed at assisting clients in managing financial assets, devising investment strategies, and outlining financial objectives. Rooted in a foundation of extensive financial knowledge and expertise, these services are tailored to each client's unique financial situation, risk tolerance, and goals, striving to deliver personalized guidance to optimize financial outcomes[7].

Table 1. Comparison between Traditional AI and Generative AI

Traditional AI	Generative AI
Executes specific tasks	Can create new data
Analyzes data and makes decisions or predictions	Uses raw data to generate new original content
Works within a set of predefined rules	Can generate text, images, music, and code
Supervised learning	Unsupervised learning
Requires labeled data for training	Does not require labeled data for training
Limited to specific tasks	Details of generated content are not controlled
Unable to create truly original content	Generated content may lack consistency or accuracy
Requires large amounts of labeled data for training	Requires large amounts of data for training

The table compares traditional AI with generative AI across various dimensions. Traditional AI focuses on executing specific tasks, while generative AI excels in creating new data and generating original content. Traditional AI relies on predefined rules, whereas generative AI can produce text, images, music, and code autonomously. In terms of learning methods, traditional AI utilizes supervised or unsupervised learning, requiring labeled data for training, whereas generative AI does not depend on labeled data. However, both types of AI have limitations; traditional AI is constrained by task specificity, while generative AI may lack control over the details of generated content. Despite these limitations, both have found applications in diverse fields, including gaming, language processing (e.g., GPT-4 by OpenAI), email filtering (e.g., Spam Sieve for Mac), artistic transformations (e.g., DeepArt), virtual assistants (e.g., Siri, Alexa), content creation, recommendation systems (e.g., Netflix, Amazon), deepfake technology, and search engines (e.g., Google).

Drawing from the principles of personalized advice and long-term financial planning, traditional financial advisory services typically adhere to the following implementation steps:

1. Client Consultation: Financial advisers engage in thorough discussions or remote interactions with clients to comprehend their financial status, objectives, and requirements.

2. Analytical Assessment: Financial advisers conduct a comprehensive evaluation of clients' financial circumstances to gauge their risk tolerance and investment objectives.

3. Advisory Services: Informed by clients' needs and objectives, financial advisers offer customized investment advice and financial planning solutions.

4. Implementation and Oversight: Upon acceptance of the advice, financial advisers aid clients in implementing the investment strategy, while regularly monitoring and adjusting portfolios to adapt to market fluctuations and evolving client needs.

5. Periodic Review: Financial advisers conduct routine review sessions with clients to evaluate investment performance and progress towards financial goals, making necessary adjustments to investment strategies as warranted.

Despite the benefits of personalized guidance and financial planning inherent in traditional services, several drawbacks exist. Firstly, [8-9]high fees associated with traditional services, including consultancy fees, management fees, and investment product charges, may pose a financial burden for some clients. Secondly, traditional services often cater to high net worth individuals or specific financial needs, potentially excluding ordinary or small-scale investors. Additionally, reliance on traditional services necessitates clients to relinquish control over their financial management, potentially leading to information asymmetry and inadequate risk management. Moreover, the sluggish response time of traditional services may impede their ability to address market changes and customer requirements promptly, hindering service flexibility and efficiency.

In light of these limitations, the emergence of AI-Powered Intelligent Financial Advisory Systems Using Generative Artificial Intelligence offers a transformative alternative. By leveraging advanced AI algorithms and generative technologies, these systems can provide personalized, efficient, and cost-effective financial advisory services to a broader spectrum of clients, addressing the evolving needs of modern investors and navigating market complexities with agility and precision.

2.3. The Role of Generative AI in Financial Advisory Services

Traditional investment advisers are tasked with understanding investors' perspectives and managing portfolios to align with their risk tolerance and market conditions. However, these tasks have historically required extensive manual effort, inadvertently creating barriers to entry for wealth management services, primarily accessible to high net worth individuals.

The advent of robo-advisors has revolutionized portfolio management by minimizing human intervention, enabling automated asset management accessible to a broader demographic.[10] Leveraging powerful computer models and artificial intelligence, intelligent investment advisers create personalized wealth portraits for a multitude of clients, tailoring asset management investment plans with precision and efficiency.

Wealthfront exemplifies this shift, leveraging machine learning and quantitative technology to offer customized asset portfolio suggestions to clients. Through questionnaires and assessments, Wealthfront determines optimal asset allocation, including stocks, stock options, debt, and real estate, thereby maximizing investment returns through automated management services.

The automated investment management process at Wealthfront follows five steps:

1. Assessment of the current investment environment to determine the ideal asset class.
2. Selection of low-cost ETFs representing each asset class.
3. Evaluation of risk tolerance to create a suitable investment portfolio.
4. Application of modern investment portfolio theory (MPT) to spread risk.
5. Regular monitoring and adjustment of the balanced portfolio.

This approach has garnered market recognition, evidenced by Wealthfront's significant growth in assets under management.

Intelligent advisers, unlike their human counterparts, can mitigate the emotional impact of market fluctuations and adhere strictly to pre-set strategies. Moreover, they offer transparent information disclosure and timely risk alerts, reducing communication barriers between asset custodians and managers. Betterment, another notable financial technology company, applies portfolio theory and financial derivative models to offer personalized asset allocation portfolios, catering to users' risk preferences.[11] Future Advisor utilizes intelligent algorithms to monitor multiple financial accounts, optimize portfolios, and identify tax-saving opportunities in real time, offering fee-based investment broker services.

In summary, generative AI is revolutionizing financial advisory services by democratizing access, optimizing investment strategies, and enhancing transparency and efficiency, in alignment with the principles of AI-Powered Intelligent Financial Advisory Systems Using Generative Artificial Intelligence.

2.4. Enhancing User Experience and Trust

As the financial landscape continues to evolve with the integration of generative artificial intelligence (AI), ensuring a seamless user experience and fostering trust are paramount for the widespread adoption of AI-powered financial advisory systems.

1.User Experience Optimization:

Streamlined Onboarding: Simplifying the initial setup process for users by minimizing the number of steps required to create an account and input relevant financial information.

Intuitive Interface: Designing a user-friendly interface that provides clear navigation and easy access to essential features, such as portfolio performance tracking and investment recommendations.

Personalized Recommendations: Leveraging AI algorithms to deliver tailored investment suggestions based on users' financial goals, risk tolerance, and market preferences.

Interactive Tools: Offering interactive tools and calculators to help users visualize the potential impact of different investment scenarios and make informed decisions.

2.Transparency and Trust Building:

Clear Communication: Providing transparent explanations of how AI algorithms work and how investment recommendations are generated to build user confidence in the system.

Disclosure of Fees: Clearly outlining any fees associated with using the financial advisory service, including management fees and investment product charges, to ensure transparency and avoid surprises.

Security Measures: [12]Implementing robust security measures to safeguard users' personal and financial information, such as encryption protocols and multi-factor authentication.

Compliance and Regulation: Adhering to industry regulations and compliance standards to instill trust in users that their investments are managed in accordance with established guidelines and best practices.

3.Continuous Improvement:

Feedback Mechanisms: Soliciting feedback from users to identify areas for improvement and address any concerns or issues promptly.

Iterative Development: Continuously updating and refining the AI algorithms and system functionalities based on user feedback and market trends to enhance performance and user satisfaction.

Educational Resources: Providing educational resources and materials to empower users with the knowledge and skills to make informed financial decisions and understand the rationale behind investment recommendations.

By prioritizing user experience optimization, transparency, and trust-building initiatives, AI-powered financial advisory systems can cultivate long-term relationships with users and position themselves as reliable and indispensable tools for achieving financial goals.

3. Methodology

3.1. Robo-Advisers (RA)

Robo-advisers, also referred to as intelligent advisers, revolutionize traditional financial advisory services by integrating artificial intelligence into the investment management process. Drawing upon portfolio theory and individual investors' unique risk preferences and financial objectives, these platforms leverage a series of artificial intelligence algorithms to offer automated investment solutions.

The concept of intelligent investment management first gained traction when introduced by Betterment in 2010. Since then, robo-advisers have garnered widespread popularity among users due to their numerous advantages, including low entry barriers, cost-effectiveness, and round-the-clock online accessibility.

$$\begin{aligned} &\mathrm{Rrob}(\mathrm{RAAdopted}_{i,T} = 1|X) = \\ &\log it\ (a_0 \\ &+a_1 \mathrm{Pre\mu ious\_In\mu estment\_Performance}_i \\ &+a_2 \mathrm{Pre\mu ious\_In\mu estment\_Characteristic}S_i \\ &+a_3 \mathrm{Controls}_i) \end{aligned} \quad (1)$$

$$\begin{aligned} &\mathrm{RAShare}_{i,T} = \beta_0 + \beta_1 \mathrm{Pre\mu estment\_Characteristic}S_i \\ &+\beta_2 \mathrm{Pre\mu ious\_In\mu estment\_Characteristic}S_i \\ &+\beta_3 \mathrm{Controls}_i + \varepsilon_i \end{aligned} \quad (2)$$

By harnessing the power of artificial intelligence, robo-advisers streamline the investment process, providing users with personalized investment strategies tailored to their specific needs and goals. This innovative approach not only democratizes access to investment management services but also enhances efficiency and accessibility, catering to the evolving needs of modern investors.

The number of defaults experienced by investors in the past, rather than the average monthly return rate, significantly affected the adoption behavior of investors, which is likely because defaults delivered a clear and distinct risk signal to investors, making investors who frequently experienced defaults believe that P2P online lending platforms have uncontrollable risks, so they are more reluctant to adopt the services of intelligent advisers. And tend to trust their own judgment.

3.2. Adjustment of RA Usage

Based on the recency effect perspective, investors exhibit a tendency to base their decisions on recent investment performance, which significantly influences their attitudes towards the utilization of smart advisers. [13]This phenomenon underscores the profound impact of recently acquired information on individual social perception, particularly evident in the financial domain where investors often overlook the cyclical nature of investment returns. Instead, they primarily adjust their investment decisions based on the recent profitability of their investments.

In this study, we employ model (3) to delve into the extent to which the usage of intelligent advisers is influenced by recency effects. Specifically, we examine two key independent variables: the investment performance achieved through the utilization of intelligent advisers in the preceding period and the investment performance attained through individual manual trading. [14]By scrutinizing these variables, our model seeks to elucidate whether investors tend to make decisions regarding the continuation of smart adviser usage primarily based on recent investment performance. Additionally, we aim to determine whether investors disregard the cyclical patterns inherent in investment returns when making such decisions.

$$\begin{aligned} &\mathrm{RAShare}_{i,t} = \beta_0 + \beta_1 \mathrm{RA\_Preformance}_{i,t-1} \\ &+\beta_2 \mathrm{Manual\_Preformance}_{i,t-1} \\ &+\beta_3 \mathrm{Controls}_{i,t} + \mathrm{Lender}_i + \mathrm{Month}_t + \varepsilon_{i,t} \end{aligned} \quad (3)$$

Through this analytical framework, we endeavor to uncover the underlying mechanisms driving investor behavior and decision-making processes in the context of smart adviser utilization. By shedding light on the interplay between recent investment performance, recency effects, and the adoption of intelligent advisers, our study contributes valuable insights to the understanding of investor behavior in financial markets.

According to the recency effect, investors tend to adjust the use of smart advisors based on defaults experienced in the previous month. [15]Specifically, investors tend to reduce their use of smart advisors when more defaults occur on their investments using smart advisors in the previous month; In contrast, when investors experienced more defaults on their personal manual investments in the previous month, they were more willing to use smart advisors' investment solutions. This behavior reflects that investors' trust in smart advisors is influenced by recent investment performance, and indicates that they tend to adjust their investment strategies to reflect the latest market conditions. This trend may be due to investors' tendency to make decisions based on recent experience and information, ignoring the importance of long-term investment performance. Thus, this finding highlights the role of recency effects in investment decisions and how investors' use of and trust in smart advisors is influenced by recent investment performance.

3.3. Performance of RA Adjustment

The adjustment of smart adviser usage based on recency effects may lead investors to make suboptimal investment decisions, ultimately affecting overall investment performance. While smart advisers typically provide solutions geared towards optimizing long-term [16]investment returns, investors who frequently adjust their usage based on recent monthly data may disrupt the long-term strategy of intelligent money management. This behavior often results in investors prioritizing short-term gains over adhering to the long-term investment strategies devised by intelligent investment advisers, thus making suboptimal investment decisions.

Model (4) primarily investigates how investors' adjustments to smart adviser usage influence their overall investment performance. The goal of this model is to unveil the impact of recency effects on investors' long-term investment performance and ascertain whether investors tend to alter their investment strategies based on recent investment performance, potentially undermining the long-term efficacy of smart advisers.

$$\begin{aligned} ReturnRate_i &= \beta_0 + \beta_1 RAShare\_Adjustment_i \\ &+ \beta_2 RAShare_i + \beta_3 Controls_i + \varepsilon_i \end{aligned} \quad (4)$$

To estimate the above model, two samples were utilized: sample (1) comprising completed investment transactions from May 2015 to June 2016, and sample (2) encompassing ongoing investment transactions. The results, as presented in Table 3, indicate that frequent enabling or disabling of smart advisers diminishes investment returns. This finding underscores how human intervention often compromises the long-term objectives of smart financial solutions, resulting in inferior performance. Notably, in the second sample covering ongoing investment transactions, the negative effects of frequent adjustments by investors to smart advisers are more pronounced. This observation underscores the importance of maintaining a consistent usage pattern of smart advisers and refraining from frequent interventions to fully capitalize on their long-term investment benefits.

This research holds significance for smart finance service providers, offering valuable insights into understanding and predicting users' adoption and usage behavior of smart advisers. [17]This understanding can aid designers in optimizing the design of smart advisers to better align with user needs and preferences. While intelligent investment advisers offer cost-effective financial plans, their focus on portfolio optimization for long-term returns may entail temporary setbacks. Thus, users require a deeper comprehension of these systems' inner workings to avoid making suboptimal investment decisions due to limited personal rationality.

Moreover, the inherent complexity of algorithms often renders intelligent systems opaque, making it challenging for users to fully grasp their operations. To address this challenge, service providers should prioritize offering more transparent services and implementing appropriate evaluation programs to enhance user trust. Additionally, they should emphasize user-friendly interaction design and develop flexible, efficient, and personalized financial investment services rooted in technology. This approach will empower intelligent advisers to better serve the public and foster a mutually beneficial relationship between users and service providers.

4. Conclusion

Based on the conclusion of the article, one potential application of artificial intelligence in the financial sector is the development and promotion of AI financial advisers. These advisers leverage AI algorithms to analyze market trading conditions and provide insights into future market trends. This advancement in technology allows financial companies to offer more personalized and efficient investment services to their clients.In conclusion, the integration of generative artificial intelligence (AI) into financial advisory services represents a transformative shift in the industry, democratizing access to personalized wealth management solutions and optimizing investment strategies for a broader spectrum of clients. [18]By leveraging advanced AI algorithms and machine learning techniques, intelligent investment advisers, exemplified by platforms like Wealthfront and Betterment, offer bespoke asset portfolio recommendations tailored to individual risk profiles and investment objectives.

The impact of users' past investment performance on their adoption of intelligent advisers underscores the nuanced interplay between past performance, risk perception, and the adoption of innovative financial technologies. While poor investment performance may lead some investors to seek assistance from intelligent advisers to enhance their outcomes, frequent adjustments to smart adviser usage based on recency effects can undermine long-term investment objectives, highlighting the importance of consistent usage patterns to fully capitalize on the benefits of these platforms.

Moreover, our research emphasizes the significance of transparency, user-friendly interaction design, and tailored financial services to foster user trust and enhance the optimization of intelligent advisers' design. By prioritizing user experience optimization, transparency, and trust-building initiatives, AI-powered financial advisory systems can cultivate long-term relationships with users and position themselves as reliable and indispensable tools for achieving financial goals.

In summary, the convergence of generative AI and finance offers immense potential to revolutionize traditional financial advisory services, empowering individuals to make informed investment decisions and navigate market complexities with agility and precision.

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