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Investor Sentiment and Satisfaction in Automated Investment: A Sentimental Analysis of Robo-Advisor Platforms

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Abstract

The rapid evolution of fintech has led to the rise of robo-advisor platforms that utilize artificial intelligence (AI) and machine learning to offer personalized investment solutions efficiently and cost-effectively. This research paper conducts a comprehensive sentiment analysis of investor experiences with these platforms, employing natural language processing (NLP) and sentiment classification techniques. The study investigates investor perceptions, engagement, and satisfaction, identifying key drivers of positive sentiment such as clear communication, low fees, consistent returns, and robust security. Conversely, negative sentiment is linked to issues like inconsistent performance, hidden fees, poor customer support, and a lack of transparency. The analysis reveals that addressing these pain points—through improved transparency, enhanced customer service, and ongoing technological advancements—can significantly boost investor trust and satisfaction. This paper contributes valuable insights to the fields of behavioral finance and fintech innovation, offering actionable recommendations for stakeholders, practitioners, and policymakers. Future research should explore the long-term impact of these factors on investor loyalty, the role of emerging technologies, and the effects of ethical investment choices and regulatory compliance on investor sentiment.

Keywords: *Artificial Intelligence in Finance, Automated Investment, Financial Technology, Investor Satisfaction, Investor Sentiment, Robo-Advisors, Sentimental Analysis.*

Introduction

The rapid advancement of financial technology (fintech) has ushered in a new era of automated investment solutions, prominently exemplified by robo-advisor platforms. These platforms leverage artificial intelligence (AI) and machine learning algorithms to offer algorithmic-based investment advice and portfolio management services to individual investors. Central to their appeal is the promise of efficient, cost-effective, and personalized investment strategies tailored to meet diverse investor needs and risk appetites.

Amidst this technological evolution, understanding investor sentiment and satisfaction has emerged as a critical determinant of the success and adoption of robo-advisor platforms. Investor sentiment, encompassing emotional responses, perceptions, and attitudes towards automated investment services, plays a pivotal role in shaping user experiences and decision-making processes. Sentimental analysis, employing techniques such as natural language processing (NLP) and sentiment classification, provides a robust framework for deciphering these nuanced aspects of investor behavior and sentiment.

This research paper aims to conduct a comprehensive sentimental analysis of investor experiences with robo-advisor platforms, exploring the multifaceted dimensions of sentiment and satisfaction. By examining how investors perceive, engage with, and respond to robo-advisor services, this study seeks to uncover underlying drivers of satisfaction, identify potential pain points, and elucidate factors influencing investor trust and confidence in automated investment solutions.

Furthermore, this research contributes to advancing knowledge in the fields of behavioral finance and fintech innovation. By integrating qualitative insights from sentiment analysis with quantitative

data, the study aims to provide actionable recommendations for enhancing robo-advisor functionalities, improving user engagement, and fostering a deeper understanding of investor preferences in automated investment environments.

The subsequent sections of this paper will review relevant literature on robo-advisor platforms and sentiment analysis, outline the methodology employed for data collection and analysis, present empirical findings, and discuss implications for both practice and future research. Through this comprehensive examination, this research endeavors to inform stakeholders, practitioners, and policymakers on strategies to optimize the effectiveness and adoption of robo-advisor platforms amidst evolving investor sentiments and preferences.

Review of Literature

The landscape of automated investment advising services has undergone a dramatic paradigm shift with the emergence of robo-advisor platforms. These platforms provide automated portfolio management solutions to individual investors based on their risk profiles and financial goals, thanks to developments in artificial intelligence (AI) and machine learning (Aggarwal, 2022). The promise of robo-advisors to democratise access to complex investing techniques that are typically only available to institutional investors, along with reduced costs and improved transparency, is a major draw for these services (Ángeles López-Cabarcos, et al 2020).

Numerous FinTech (Financial Technologies) have developed to upend the entire sector. One of the more recent FinTech innovations is robo-advisors, which are gaining popularity by promising a number of possible benefits like cost savings and transparency for the financial services sector. However, it's still too early to determine if what we're hearing is genuine or not. There is conflicting and mixed anecdotal data and views regarding the likelihood that Robo-Advisors may soon join other disruptive FinTech companies. Ngo-Ye et al (2018) study makes the case that trust is a key element influencing the uptake and eventual success of robot advisors. It details how an agent-based simulation model was created to investigate the effects of important components in the processes involved in establishing trust.

The paper by He et al (2022) builds a media-based investor sentiment index by examining the content of the top financial publications in China. To gauge the overall literary tone of the media news, they use both the dictionary method and the Word2Vec technique. Overall, the results suggest that news coverage in the media is a valuable source of information for gauging the general sentiment of investors, which influences short- and long-term movements in future stock prices.

The research of Valle-Cruz et al (2022) shows how crucial investor trust and pleasure are to the uptake and success of financial technologies like robo-advisors. According to Xing et al (2020); Aggarwal (2022) customer satisfaction is frequently correlated with perceived value for money, convenience of use, and service quality. Conversely, trust is based on elements like platform openness, the accuracy of investing guidance, and the protection of private financial data.

An article by PH & Uchil (2020) states that a rapidly expanding field of study is the incorporation of sentiment analysis methods into fintech applications, such as robo-advisor systems. Sentiment analysis analyses textual data, such as investor reviews and feedback, to extract emotional cues and sentiments using natural language processing (NLP) and machine learning algorithms. The study by Feng et al. (2020) reveals that Robo-advisors can improve user happiness by managing customer expectations, personalising financial advice, and quantifying and analysing investor sentiment.

A article by Zhou (2018) examined a range of investor sentiment metrics derived from market, survey, text, and media data. There's no shortage of data to support the idea that sentiment can account for returns on equities that are hard to assess and expensive to arbitrage, like distressed, extreme growth, non-dividend paying, and unprofitable businesses. Still, a lot of work needs to be done. The three study directions covered in this paper are statistical modelling of investor sentiment evolution, connecting investor sentiment to technical analysis,

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and aggregating measures spanning different sources and time ranges. The results concluded that both investor sentiment and the asset values derived from their economic fundamentals fluctuate in tandem with asset prices. Assessing investor sentiment is crucial for both practical investing and theoretical asset pricing. Wankhade et al (2022) paper offers a thorough description of sentiment analysis techniques and uses. It assesses and contrasts various strategies to fully comprehend their advantages and disadvantages. It also looks at the difficulties in sentiment analysis to determine areas that need development in the future.

Proposed Methodology

The sentiment analysis process is illustrated in Figure 1 and detailed in the following sections.

A) Data Collection and Respondents Profile

Using Google Forms, primary data for this study was collected. Investors who have utilised robo-advisor services was interviewed in an organised manner in order to gather data. The purpose of these interviews were to get in-depth information on their experiences, including their opinions, degrees of happiness, and feelings regarding different elements of the platforms. Open-ended interview questions have ben used to elicit a variety of opinions and perspectives. In order to generate a text corpus for study, the responses were transcriptions. The invitation was sent through mails which guaranteed response secrecy and anonymity while outlining the goals of the study. Out of 200, feedback from 150 investors using robo-advisor services was received.

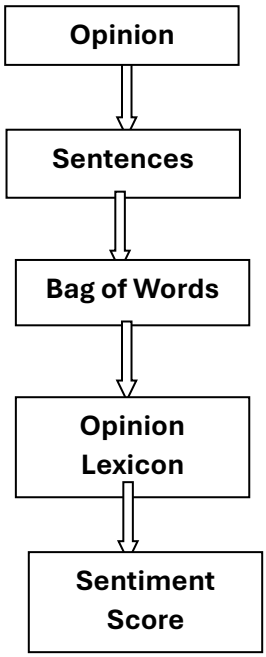

Fig.1: Lexicon-based sentiment analysis approach

B) Data Cleaning

Textual data first underwent data cleansing in order to be ready for sentiment analysis. In order to guarantee accurate and trustworthy analysis results, it entails locating and fixing problems within the dataset. Important facets of data cleansing consist of:

- Deleting extraneous symbols, HTML tags, special letters, and punctuation to make room for valuable information.
- Normalising the text means eliminating accents and changing it to lowercase. Eliminating stop words, which are popular words that lack emotional significance.
- Removing emojis and Emoticons.
- Fixing Spelling errors in the text.

C) Sentiment Orientation Identification

A key component of sentiment analysis is identifying sentiment orientation, which focuses on

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identifying the polarity or direction of the attitude indicated in the text and categorising it as positive, negative, or neutral. Opinion Lexicons (Hu and Lin, KDD-2004) were used in this study to categorise sentiments. A score of +1 was given to positive words, a score of -1 to negative words, and a score of 0 to neutral terms. The sum of the ratings for each adjective in a review was used to calculate the overall review score. Reviews were categorised as positive or negative depending on the score, and as neutral or negative depending on the score. The sentiment score as a whole was 40 and 37. A word cloud was also created to display the positive frequency.

```
positive<-scan("positive.txt", what="character", comment.char = ";")
negative<-scan("Negative.txt", what="character", comment.char = ";")
head(positive)
head(negative)
senti_analysis<-unlist(clean_data7)
match(senti_analysis, positive)
match(senti_analysis, negative)
p_score<-sum(!is.na(match(senti_analysis, positive)))
p_score
n_score<-sum(!is.na(match(senti_analysis, negative)))
n_score
Sentiment_score= p_score- n_score
Sentiment_score
```

Fig.2: Code to Generate the Sentiment Score in R Programming

Results and Discussion

User happiness and trust are highly dependent on how well the robo-advisor platform communicates, especially when it comes to elucidating investment methods and results. 34 people offered negative input on this topic, while 74 individuals gave favourable comments, per the sentiment analysis. The platform's communication effectiveness is seen favourably overall, as indicated by the question's overall sentiment score of 40.

```
> p_score<-sum(!is.na(match(senti_analysis, positive)))
> p_score
[1] 74
> n_score<-sum(!is.na(match(senti_analysis, negative)))
> n_score
[1] 34
> Sentiment_score= p_score- n_score
> Sentiment_score
[1] 40
```

Fig.3: Code to Generate the Sentiment Score in R Programming

The data supplied indicates that cheap fees in comparison to traditional advisors, clear and honest information about investment plans, and consistent positive returns on investments are the elements that favourably impacted user opinion towards the robo-advisor platform. The user-friendly interface, tailored investment suggestions, excellent customer service, and frequent updates on market conditions and portfolio performance were also well-liked by users. Positive contributions were also made by the platform's high degree of automation, security features, and interaction with other financial tools. Furthermore, well-liked features included customisable risk settings, performance tracking, educational materials, and the availability of human advisors with experience. The clear price schedule, happiness with ethical and sustainable investment options, precise financial forecasts, and ongoing algorithmic development were all highly regarded by users. The availability of retirement planning

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tools, prompt notifications, diversification tactics, assurance of regulatory compliance, creative tools for portfolio rebalancing, simple withdrawal procedures, socially conscious investment options, and frequent feature updates were other beneficial aspects.

Fig. 4: Creation of Word Cloud using R Programming with min frequency 3 times a word

On the other hand, a number of variables adversely affected user opinion. These included erratic investment returns, opaque decision-making processes, exorbitant fees that lowered investment rewards, and subpar customer service with lengthy wait times. In addition, users bemoaned a difficult-to-use interface, regular technical difficulties, a lack of information regarding market conditions, and a small number of unsatisfactory investment possibilities. Other negative issues were automated decisions that were out of line with their risk tolerance, delayed updates on portfolio performance, erroneous performance reports, and a lack of personalisation in investing suggestions. Negative opinion was further exacerbated by inadequate instructional resources, unstated costs, trouble reaching customer assistance, and difficulties transferring or withdrawing money from accounts. User satisfaction was also adversely impacted by worries regarding the platform's regulatory compliance. Resolving these problems could enhance overall user experience and sentiment towards the platform.

Conclusion

This research paper's comprehensive sentiment analysis reveals that while robo-advisor platforms offer significant advantages such as cost efficiency, personalized investment strategies, and user-friendly interfaces, there are also notable areas for improvement. Positive sentiment is driven by factors like clear communication, low fees, consistent investment returns, robust security, and innovative features. However, issues such as inconsistent performance, high hidden fees, poor customer support, and lack of transparency negatively impact user satisfaction. Addressing these pain points through enhanced transparency, improved customer service, and continual technological advancements can significantly improve investor trust and satisfaction. This study provides valuable insights for stakeholders, highlighting the need for a

balanced approach to maintaining user engagement and trust while leveraging the efficiencies and innovations of robo-advisor platforms.

Implications

Robo-advisor platforms need to concentrate on enhancing communication transparency, guaranteeing consistent investing performance, and keeping costs low in order to increase investor happiness and trust. It's also essential to improve customer service, streamline the user interface, and offer tailored investment advice. User satisfaction will increase even more if technical difficulties are resolved quickly and accurate information on market conditions and portfolio performance are provided on a regular basis. This work makes a contribution to the domains of fintech innovation and behavioural finance by combining quantitative data with sentiment analysis to produce useful insights. Future studies could examine how these variables affect investor loyalty over the long run and how new technology affect robo-advisor systems. Further insights may be obtained by looking into how ethical investment choices and regulatory compliance affect investor opinion.

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