

Designing and Implementing an Artificial Intelligence-Based Robo-Advisor to Assess Investors' Risk Tolerance: A Case Study of the S&P 500 Index

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ABSTRACT

Financial services companies such as banks, brokerage firms, family offices, insurance companies, and trusts, provide advisory services to help clients achieve their investment goals. These services typically include offering investment solutions and discretionary portfolio management, where asset management is entrusted to financial experts. One of the main challenges in this field is recommending investment strategies that align with clients' needs and risk tolerance. In this study, a model was designed to assess investors' risk tolerance using advanced artificial intelligence (AI) and machine learning techniques. The model analyzed investors' demographic and financial data using regression algorithms to calculate their risk profiles. Then, an intelligent robo-advisor was designed to recommend the most suitable investment mix in S&P 500 companies' stocks based on individual investor profiles. The data for this study was extracted from the Federal Reserve's Survey of Consumer Finances (SCF), conducted between 2007 and 2009. The results of this research indicated that the use of AI and machine learning models can significantly improve the accuracy of assessing investors' risk tolerance. The proposed model, utilizing demographic and financial data from the SCF, successfully generated diverse risk profiles for investors. The designed robo-advisor intelligently analyzed these profiles and provided appropriate investment strategies for the S&P 500 index.

KEYWORDS

Artificial Intelligence, Investment Advisory, Investment Portfolio, Machine Learning, Risk Tolerance, Robo-Advisor.

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Introduction

In today's financial world, investment advisory plays a crucial role in helping investors achieve their financial goals. However, providing advice that accurately addresses investors' needs while considering their risk tolerance has always been a significant challenge in wealth management. The emergence of new technologies, particularly artificial intelligence (AI) and machine learning, has led to remarkable advancements in this field, giving rise to innovative solutions such as robo-advisors. Robo-advisors use advanced algorithms and analyze financial and demographic data to provide automated and personalized investment recommendations to investors, offering both simplicity and high accuracy (Torno et al., 2021; Grealish & Kolm, 2021).

As financial markets become increasingly complex and both retail and institutional investments expand, traditional financial advisory services face limitations. On one hand, the growing number of investors and, on the other, the diversity of investment behaviors, require financial advisors to evaluate investors' risk tolerance more accurately (Darskuvienė & Lissauskienė, 2021). In this context, robo-advisors, with their ability to quickly and intelligently analyze financial and psychological data, can effectively manage these challenges and offer optimal recommendations to investors (Jung et al., 2019).

In this research, leveraging recent advancements in AI and machine learning, a new model for assessing investors' risk tolerance has been developed. This model analyzes data from the Survey of Consumer Finances (SCF) and uses regression algorithms to create personalized risk profiles for investors. Subsequently, by implementing an intelligent robo-advisor, appropriate investment strategies for stocks in the S&P 500 index are recommended. This study examines how this system can be integrated within investment advisory and portfolio management firms, evaluating its impact on the accuracy and efficiency of the financial advisory process.

Literature Review

Robo-advisors are digital platforms that provide algorithm-based, automated financial planning services, such as investment management. These services do not require human supervision due to their autonomous capabilities. Robo-advisors collect information about clients' financial situation and future goals. To do this, they are typically asked to respond to a survey or answer several online questions. The data entered is then used to provide tailored financial advice.

Robo-advisor software asks investors questions regarding their financial situation and goals, and based on their responses, algorithms are often employed to provide recommendations on buying, selling, or holding certain products. The advice generated depends on the client's input and the algorithmic logic used to determine which type of recommendation is appropriate based on the information. The tool can be represented as a decision tree, where the client follows a series of questions to arrive at a

recommendation. Some robo-advisors are fully automated, while others incorporate human interactions at certain stages of the advisory process.

Robo-advisors fundamentally change the investment advisory process. Beyond the nature of interaction, they also bring changes in the format of information and contracts. When investment decisions are made online, there is typically no human present to ensure that the investor has fully understood the information provided or that the responses given were appropriately evaluated. No one is available to briefly review the meaning of the content (Salo & Haapio, 2017). Table 1 provides a comparison between Robo-Advisors, Portfolio Management, and Mutual Funds.

Table 1.
Comparison between Robo-Advisors, Portfolio Management, and Mutual Funds

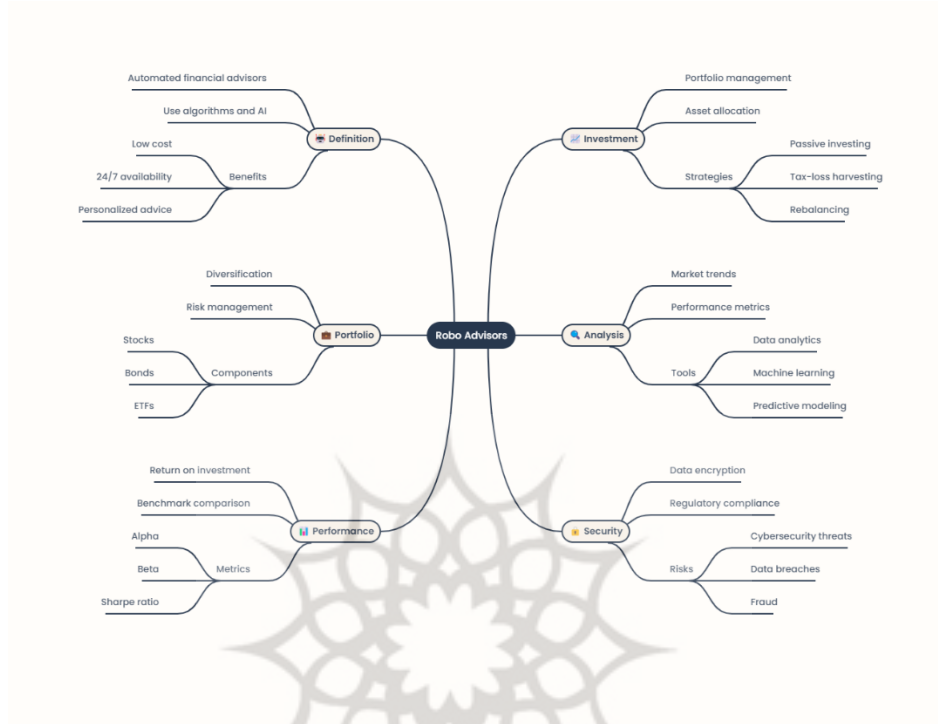
Feature	Robo-Advisors	Portfolio Management	Mutual Funds
Definition	Automated platforms using algorithms to manage portfolios	Professional management of individual portfolios	Pooled investment vehicles managed by fund managers
Management Style	Algorithm-based, passive or hybrid strategies	Custom, personalized management by professionals	Active or passive strategies by fund managers
Customization	Limited, based on user inputs like risk tolerance	High, tailored to individual needs and goals	Limited, using the same portfolio for all investors in the fund
Fees	Low (0.25%–0.50% annually)	High (1%–2% or more annually)	Moderate (0.5%–2% annual expense ratio)
Investment Strategy	Primarily passive (index-based ETFs)	Can be both active or passive	Active or passive depending on the fund type
Minimum Investment	Low (\$500 or less in some cases)	High (Typically \$100,000 or more)	Varies (can be low or high, often \$1,000–\$3,000)
Human Interaction	Minimal or none, customer support available	High, direct contact with a portfolio manager	None or limited, no direct contact with fund managers
Accessibility	Easy, available to beginners with low capital	Less accessible, typically for high-net-worth individuals	Moderately accessible for individual investors
Transparency	High, with real-time portfolio updates	High, frequent reporting and direct insights	Moderate, detailed quarterly reports but no daily insights
Risk Level	Managed based on user's risk profile	Adjusted for individual risk tolerance	Depends on the fund's objective (can vary from low to high)
Tax Efficiency	Moderate, some tax-loss harvesting options	High, can be tailored for tax efficiency	Varies, generally less tax-efficient due to pooled structure
Rebalancing	Automatic, often periodically (e.g., quarterly)	Manual, based on professional judgement	Periodic, at the discretion of the fund manager
Suitable for	Beginners or investors preferring low-cost, automated solutions	High-net-worth individuals needing personalized service	Investors seeking diversification in a single product
Time Commitment	Minimal after setup	Requires regular consultation with manager	Minimal, once invested
Examples	Betterment, Wealthfront	Private wealth managers, financial advisors	Vanguard, Fidelity, BlackRock mutual funds

(Source: Researcher's Findings)

In the chart below, the various applications of robo-advisors are illustrated.

Figure 1.

The various applications of robo-advisors



(Source: <https://mylens.ai/space/aq4phi8nnmt/story/robo-advisors-in-investment-M6yGWW?slide=10>)

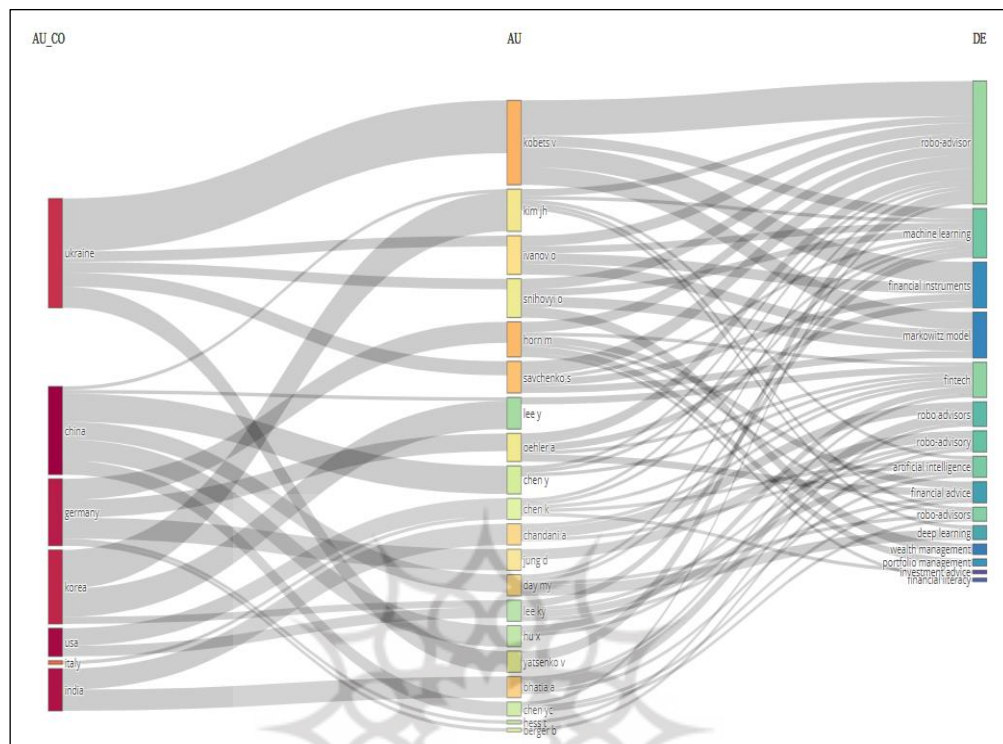
So far, limited research has been conducted on "robo-advisors". To gain a better understanding of the application of recommendation systems in finance, the keyword "in investment robo-advisors" was searched on Scopus on October 22, 2024, and the following outputs were obtained using the bibliometrix package in R. According to the Scopus database, there are only 177 documents on this subject, of which 89 are articles under this title. A summary of the descriptive statistics is as Table 2.

Table 2.

A summary of the descriptive statistics of robo-advisors

Results	Description
Main Information About Data	
2017:2024	Timespan
138	Sources (Journals, Books, etc.)
176	Documents
26.44	Annual Growth Rate %
2.69	Document Average Age
12.38	Average citations per doc
0	References
Document Contents	
631	Keywords Plus (ID)

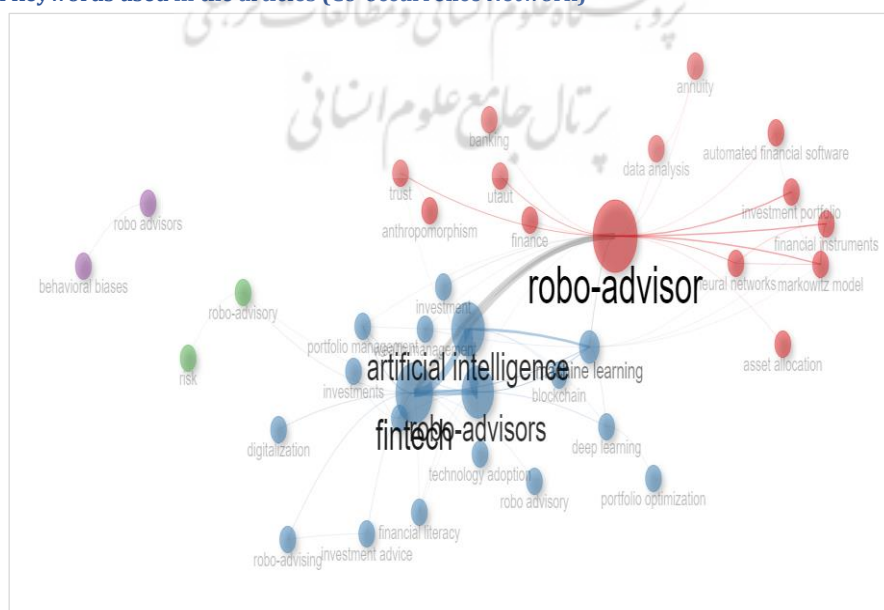
Figure 3.
The Importance of Robo-Advisors in the Conducted Research



(Source: Researcher's Findings)

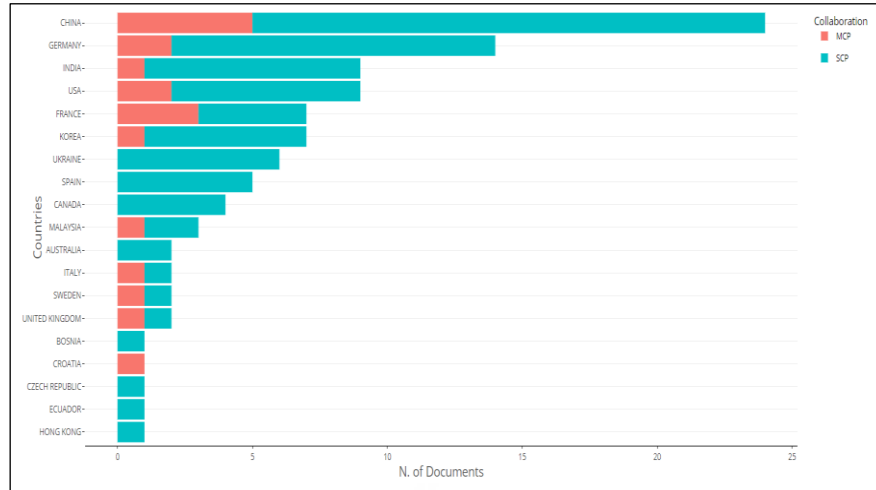
The network of keywords used in the articles is shown in the Figure 4 and Figure 5 shows Corresponding Author's Countries.

Figure 4.
The network of keywords used in the articles (Co-occurrence Network)



(Source: Researcher's Findings)

Figure 5.
Corresponding Author's Countries



(Source: Researcher's Findings)

Robo-advisors represent a transformative shift in investment management, utilizing AI to provide personalized financial advice and portfolio management with minimal human intervention. These platforms leverage big data analytics and machine learning to optimize investment strategies, adapt to real-time market conditions, and enhance investor confidence. However, challenges such as data inaccuracy and the risk of overfitting in the models must be addressed to improve their reliability and performance (Needhi et al., 2024; Ablazov et al., 2024).

Key Features of Robo-Advisors:

- *Personalized Investment Strategies:* Robo-advisors analyze individual financial goals and risk tolerance to create tailored investment plans (Ablazov et al., 2024).
- *Real-Time Data Integration:* By prioritizing real-time data, these platforms can adapt to market changes and provide timely recommendations (Needhi et al., 2024).
- *User-Friendly Interfaces:* Effective design and transparency are crucial for building user trust and encouraging adoption (Huang et al., 2024).

Challenges to Adoption:

- *Financial Literacy:* A lower level of financial literacy can hinder the acceptance of robo-advisory services (Suhaily et al., 2024).
- *Perceived Risks:* Concerns regarding data security and investment performance can discourage potential users (Suhaily et al., 2024).

While robo-advisors offer significant advantages in democratizing investment management, their effectiveness relies on addressing users' concerns and enhancing their trust in these automated systems.

The Table 2 captures the insights and findings of Robo-Advisors and their significance in the investment landscape, as outlined by various authors.

Table 3.
Insights and findings of Robo-Advisors

Authors	Insights	Key Findings
(Jeyadev, Ram, Mohamed, & Manokar, 2024)	Robo-Advisors utilize AI for strategic investment decisions, optimizing portfolios through big data analysis and deep learning.	- Real-time data integration enhances Robo-Advisors' performance. - Reduced reliance on historical data improves recommendation accuracy.
(Suhaily, Manaf, Amin, & Zakaria, 2024)	Factors influencing the adoption of Robo-Advisors include financial literacy, perceived risk, and trust.	- Key factors: financial literacy, perceived risk, perceived trust. - Informing interventions can boost financial engagement.
(Ablazov, Qodirov, Ibragimova, & Akhmedov, 2024)	Robo-Advisors enhance personal investment management using AI, offering tailored solutions compared to traditional human advisors.	- AI improves investment management efficiency and accessibility. - Robo-Advisors often outperform traditional human advisors in investment outcomes.
(Huang, Che, Zheng, & Li, 2024)	Robo-Advisors use AI algorithms for personalized investment plans, optimizing asset management and increasing user trust.	- Continuous use of smart advisors is crucial for long-term benefits. - Transparency and tailored financial services boost user trust and optimization.
(Adji, Karmawan, & Lusianah, 2024)	Robo-Advisors analyze market data and client profiles to create tailored portfolios, enhancing investor satisfaction.	- Positive relationship between Robo-Advisor use and investor satisfaction. - UTAUT variables impact investor satisfaction with Robo-Advisors.
(Liu, Xu, Qian, Zhong, & Qin, 2024)	Robo-Advisors manage investments primarily in index funds and ETFs, providing low costs and accessibility for various investors.	- AI enhances investment decision-making but presents challenges. - AI technology has significant potential in quantitative finance investments.
(Azzahra, & Rimenda, 2024)	Robo-Advisors help Millennials make informed investment decisions by facilitating risk profiling, financial planning, and rebalancing.	- Robo-Advisors effectively influence Millennials' investment decisions. - Risk profiling and rebalancing significantly impact investment choices.
(Bianchi, & Brière, 2024)	Robo-Advisors suggest investment strategies and rebalancing, increase investor attention and trading activities, and improve portfolio returns.	- Robo-Advisors increase investor attention and trading activity. - Following Robo-Advisor alerts leads to higher portfolio returns.
(Jiang, Qian, Fan, Ding, & Li, 2024)	Robo-Advisors, using modern portfolio theory algorithms, automate wealth management and offer personalized asset allocation and investment strategies.	- It highlights the transformative potential of AI in finance. - It recommends professional advice to manage compliance risks.
(Chen, 2023)	AI enhances Robo-Advisors by automating financial management, improving model efficiency, and enabling intelligent asset allocation based on risk preferences.	- Models demonstrate good profitability and risk control capabilities. - Models offers guidance for investors in quantitative investing.
(Fatima, & Chakraborty, 2024)	This study identifies performance optimism as a key factor influencing investors' adoption of Robo-Advisors, emphasizing AI's role in improving perceived effectiveness and reliability in financial decision-making.	- Trust, anxiety, performance optimism, and preference affect Robo-Advisors' adoption. - PLS-SEM with 445 investors shows significant variable roles.
(Nourahmadi et al., 2024)	Stock recommendation systems can help investors make informed decisions and achieve higher returns on investments.	- Collaborative filtering algorithms effectively identify valuable stocks for higher market returns. - Future research need to evaluate algorithm performance in diverse markets.
(Zarei et al., 2023)	It emphasizes the importance of designing and implementing intelligent financial robots, showcasing the role of machine learning algorithms in delivering personalized and efficient investment suggestions.	- This study provides a framework for developing intelligent robots in Iran, highlighting AI-driven approaches that enhance financial services.

(Source: Researcher's Findings)

The of AI in robo-advisors' Performance

AI plays a crucial role in enhancing the performance of robo-advisors by enabling personalized investment strategies, optimizing portfolio management, and improving user interaction. The integration of AI technologies allows these platforms to analyze vast amounts of financial data, leading to more informed decision-making and improved investment outcomes.

Personalized Financial Advice:

- AI algorithms analyze individual user data to tailor investment strategies, ensuring alignment with personal financial goals (Ablazov et al., 2024).
- Platforms like Wealthfront utilize AI to create customized asset management plans, enhancing user engagement and satisfaction (Huang et al., 2024).

Risk Assessment and Portfolio Management:

- AI enhances risk assessment by processing real-time market data, enabling robo-advisors to adapt to changing conditions and provide timely recommendations.
- Advanced machine learning techniques improve the accuracy of predictions related to market trends and consumer behavior (Beck, 2021).

User Experience and Trust:

- User interface design and transparency in AI operations are critical for building trust in robo-advisors (Huang et al., 2024).
- Continuous refinement of data integration methods helps maintain reliability and investor confidence (Needhi et al., 2024).
- Conversely, while AI significantly enhances the capabilities of robo-advisors, challenges such as data inaccuracy and the risk of overfitting in the models remain critical concerns that need to be addressed to ensure optimal performance and ethical standards in automated investment platforms (Needhi et al., 2024).

Comparison of Robo-Advisors and Traditional Financial Advisory Services

The emergence of robo-advisors has transformed the wealth management landscape, creating new opportunities and challenges for traditional investment advisors. Robo-advisors, which use algorithms and automation to provide personalized investment recommendations, are increasingly positioned as a low-cost alternative to human advisors. Uhl and Rohner (2018) argue that the competition between robo-advisors and traditional advisors is inherently unequal, particularly due to the scalability and affordability of robo-advisors, which allow them to serve a broader range of clients at lower costs. However, Meyll (2020) suggest that while robo-advisors can serve as a substitute for human financial advice, their capabilities in providing comprehensive financial planning and emotional support in complex financial situations are limited.

Moreover, the ability of robo-advisors to efficiently process large volumes of data has led to their acceptance among tech-savvy and cost-sensitive investors. Phoon and Koh

(2018) state that robo-advisors play an important role in democratizing access to wealth management, especially for individuals who do not meet the minimum asset requirements of traditional advisors. This shift has been particularly appealing to younger generations interested in technology-driven solutions. However, Lam (2016) believes that while robo-advisors excel in portfolio management through algorithms, they still fail to provide complex financial solutions that require human judgment.

Ultimately, while robo-advisors have successfully challenged traditional financial advisory services by offering low-cost and scalable solutions, they have specific limitations. Investors seeking straightforward portfolio management may benefit from robo-advisors, but those requiring comprehensive financial planning and personalized advice will continue to recognize the value of human advisors. (Figure 6)

Figure 6.

Comparison of robo-advisors and traditional advisor

 Advisor Type	 Cost	 Investment Strategy	 Availability	 Personalization	 Performance Tracking	 Regulation
Robo-Advisor	Low fees, often 0.25%-0.50% of AUM	Algorithm-based, passive investing	24/7 online access	Limited, based on algorithms	Automated, real-time updates	Subject to financial regulations
Traditional Advisor	Higher fees, often 1%-2% of AUM	Personalized, active investing	Business hours, in-person meetings	High, tailored to individual needs	Manual, periodic updates	Subject to financial regulations

(Source: <https://mylens.ai/space/aq4phi8nnmt/story/robo-advisors-in-investment-M6yGWW?slide=3>)

Methodology

This research aims to develop a machine learning model to predict investor risk tolerance and to utilize this model in the robo-advisor dashboard. The data used for this research comes from the Survey of Consumer Finances (SCF) conducted by the Federal Reserve Board. This survey includes responses regarding household demographic statistics and net financial and non-financial assets for 2007 (before the crisis) and 2009 (after the crisis). This allows us to observe changes in the way each household allocated its resources after the 2008 global financial crisis.

The dataset contains 19,285 observations with 515 columns. The number of columns indicates the number of features.

The steps for preparing the predicted variables are as follows:

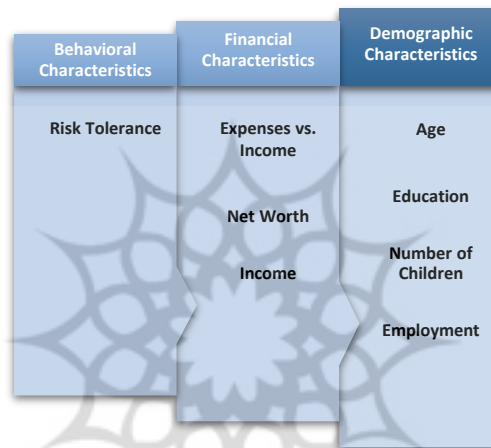
a) Calculating risky and risk-free assets for all individuals in the survey data. Risky and risk-free assets are defined as follows:

- *Risky assets*: Estimate investments in equity mutual funds, bonds, commodities, real estate, and human capital.
- *Risk-free assets*: Balances in checking accounts, savings, certificates of deposit, and other cash and cash equivalents.

b) Calculating the ratio of risky assets to the total assets of the investor and consider it as a measure of risk tolerance. In the financial literature, savvy investors do not change their risk tolerance when market conditions change. Therefore, investors who change their risk tolerance by less than 10% over time are considered savvy investors. However, this is a qualitative measure and is subject to change.

We will first calculate the risk tolerance for each of the years 2007 and 2009 and then consider the average of these as the measure of risk tolerance. In the next step, we will reduce the features. We will then use only these selected features.

Figure 7.
Flowchart



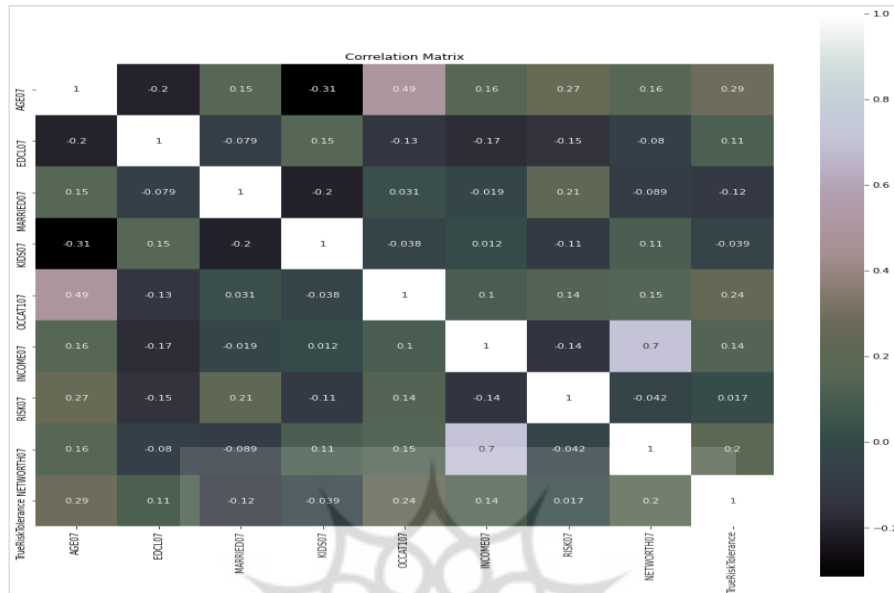
(Source: Researcher's Findings)

- *Age (AGE)*: Represents the age range of individuals, where 1 indicates an age under 35 years and 6 indicates an age over 75 years.
- *Education (EDUC)*: Represents the education level of individuals, where 1 indicates illiterate and 4 indicates a university degree.
- *Marital Status (MARRIED)*: Indicates the marriage status of individuals. There are two categories: 1 indicates married, and 2 indicates single.
- *Occupation (OCCU)*: Indicates the occupational group, where 1 represents managerial positions, and 4 indicates unemployed.
- *Number of Children (KIDS)*: Indicates the number of children.
- *Net worth Classification (NWCAT)*: Represents the classification of net worth, where 1 indicates net worth less than 25%, and 5 indicates net worth over 90%.
- *Income Level (INCCL)*: Indicates income, with 5 categories where 1 represents income under \$10,000, and 5 represents income over \$100,000.
- *Risk Tolerance (RISK)*: Indicates willingness to take risks on a scale of 1 to 4, where 1 indicates the highest level of risk tolerance.

These factors will be retained from the questionnaire, while the remaining items will be discarded.

The chart below shows the correlation between these features:

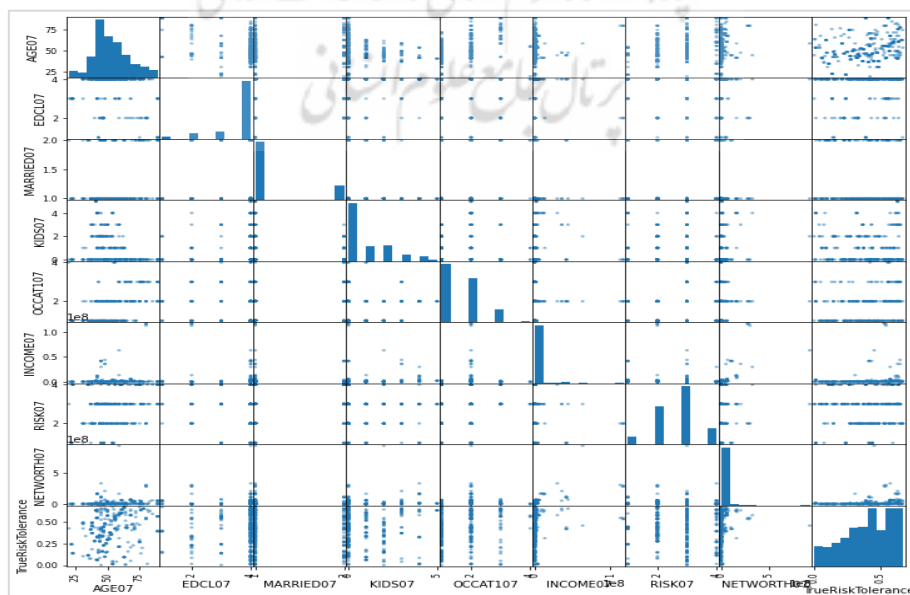
Figure 8.
Feature Correlations



(Source: Researcher's Findings)

The above correlation chart shows that net worth and income have a positive relationship with risk tolerance. As the number of children and marital status increase, risk tolerance decreases. Additionally, a decrease in willingness to take risks correlates with a decline in risk tolerance. Conversely, there is a positive relationship between age and risk tolerance, meaning that as age increases, risk tolerance tends to rise.

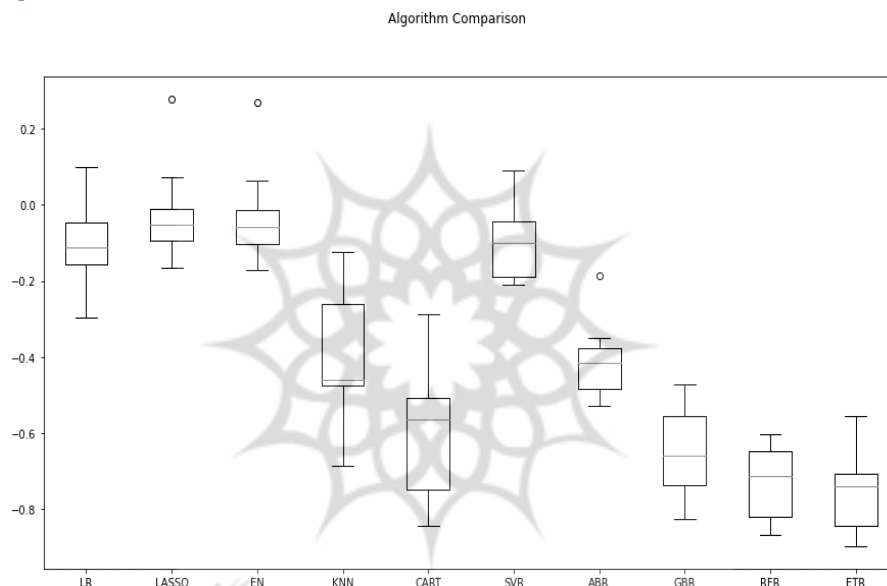
Figure 9.
Scatter plot



(Source: Researcher's Findings)

In the next step, we evaluated the model and algorithm. To do this, the data were divided into two categories, namely training and testing datasets. 20% of the data were considered as the test set. The dependent variable was the level of risk tolerance, while the other variables were treated as independent variables. For evaluation, we used boosting models (AdaBoost and Gradient Boosting), bagging models (Random Forest and Extra Trees Regression), linear regression, LASSO, Elastic Net, K-Nearest Neighbors regression, Decision Tree Regression, and Support Vector Regression (SVR). We evaluated these methods using the K-fold cross-validation technique.

Figure 10.
Algorithms Comparison

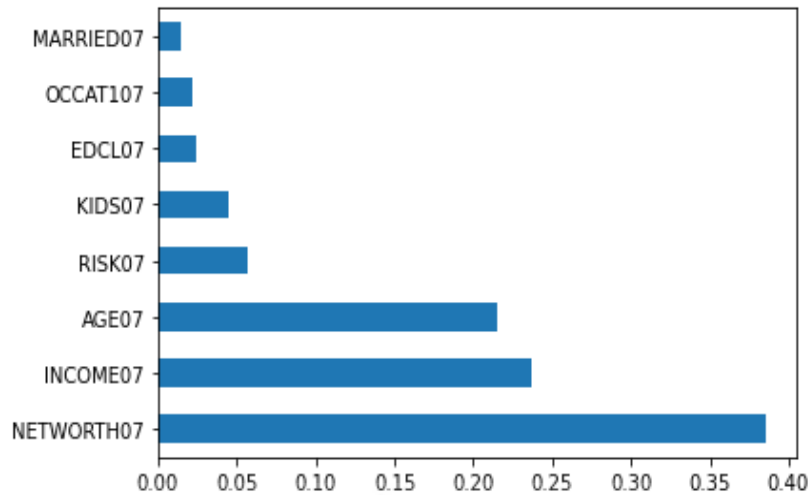


(Source: Researcher's Findings)

Non-linear models perform better than linear models, indicating a non-linear relationship between risk tolerance and other variables. Based on the results obtained, Random Forest regression emerges as one of the best methods, which we will use for further estimation of the model. For model tuning, we estimate the model over time periods of 50, 100, 150, 200, 250, 300, 350, and 400 days, with the results indicating that a 250-day window is the most suitable.

Ultimately, the model's accuracy, measured by the R^2 criterion, is found to be 0.76, while the error, calculated using the Mean Squared Error (MSE), is calculated at 0.0077. In the next step, we will determine the importance of each feature in the Random Forest model.

Figure 11.
The Importance of Each Feature



(Source: Researcher's Findings)

Based on the above chart, income and net worth, followed by age and risk preference, are the primary variables for risk tolerance. These variables are considered key indicators of risk tolerance in various studies.

Findings

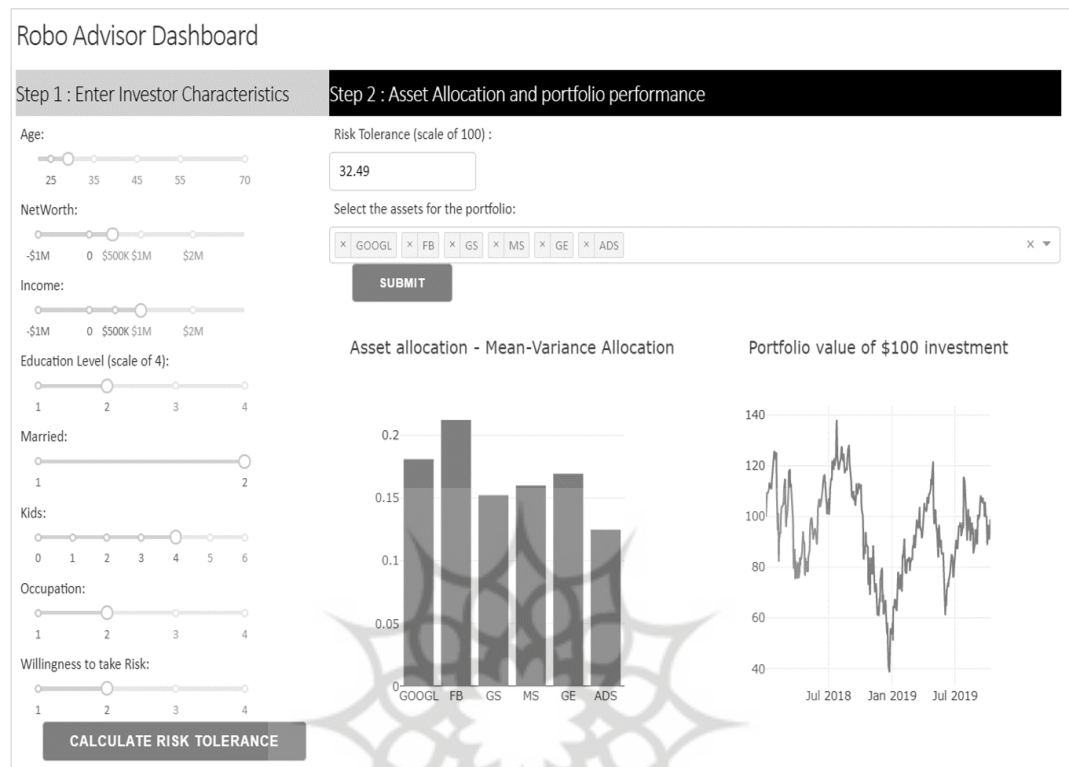
Then, we designed the Robo-Advisor dashboard using the Dash library in Python. It consists of two pages:

1. *Investor Characteristics Input*: The first section allows users to enter the investor's characteristics.
2. *Asset Allocation and Portfolio Performance*: The second section uses the mean-variance method to focus on asset allocation and portfolio performance.

The input for this model comprises the same characteristics tested in the previous section. After submitting the input, the risk tolerance was calculated, and in the next step, the desired stocks were selected and introduced to the model. The model then calculated the proportion of each of these stocks based on the personality traits and risk tolerance established in the previous stage.

Finally, the dashboard displayed the historical performance of this portfolio based on an initial investment of \$100.

Figure 12.
Robo-Advisor Investment Dashboard



(Source: Researcher's Findings)

Discussion and Conclusion

This research demonstrated that machine learning models can analyze the behavior of various investors in changing markets and examine the impact of these changes on the determinants of risk appetite. The results revealed complex and nonlinear relationships between individual variables and risk tolerance, with the most significant variables being income, net worth, age, and risk preference. These findings suggest that by utilizing machine learning models, more accurate patterns of investor behavior can be extracted and leveraged for optimizing financial decision-making.

Future Research Direction

Here are some suggestions for further research and future work:

1. *Utilization of Broader and More Realistic Data:* One of the limitations of this research was the restricted access to data from asset managers and brokerage firms. It is recommended that investment companies develop similar models using their operational data to analyze customer behavior and implement risk tolerance dashboards as decision-making tools.
2. *Expansion of Portfolio Optimization Approaches:* This study employed the mean-variance method for portfolio optimization. Future researchers and financial

analysts can utilize more complex approaches, such as Value at Risk (VaR) optimization or genetic algorithms, to enhance stock portfolio optimization and achieve more accurate results.

3. *Use of Nonlinear and Advanced Methods in Risk Models:* The research results indicated that the relationships between personal variables and risk tolerance are nonlinear. Therefore, employing more advanced methods, such as neural networks or deep learning-based models, could improve predictions and provide more precise analyses.
4. *Integration of These Models with Digital Financial Platforms:* Investment firms can leverage machine learning models to build smart financial platforms that offer investment suggestions based on customer risk profiles. Such platforms can play a crucial role in enhancing investment efficiency and customer satisfaction.

This research demonstrates that applying machine learning models in analyzing investor risk tolerance and optimizing portfolios can significantly improve the accuracy and efficiency of financial decision-making, thereby aiding investment firms in providing better services to their clients.



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