The impact of AI-driven robo-advisors on decision-making process and personalization of investors

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This study examines the role of AI-driven robo-advisors in improving personalization and decision-making processes for investors in financial markets. Through a literature review, the research synthesizes findings from academic papers, case studies, and book chapters, addressing the primary research question of how robo-advisors enhance investment decision-making and personalization. The results reveal that AI personalization technologies, categorized as Mechanical AI, Thinking AI, and Feeling AI, significantly improve customer satisfaction by tailoring investment strategies to individual preferences, financial goals, and risk tolerance. Personalization positively impacts the customer journey by fostering trust and loyalty in financial services. However, ethical concerns, such as data privacy and algorithmic bias, might be present in the AI. In terms of decision-making, the study identifies used AI models which optimize portfolio management through predictive analytics and real-time adaptability. Robo-advisors proves to be efficient in investment decisions with positive results. Key findings include a 30% improvement in portfolio performance when employing genetic algorithms through advanced AI models, such as key performance indicator (KPI) predictors and hybrid systems.

Additional Key Words and Phrases: AI, Robo-Advisor, Personalization, Recommendation, Investment

1 INTRODUCTION

Financial markets are responsible for playing a crucial role in the economy, specifically the stock market, which provides funds for companies to grow and allows investors to share the business‘ profit [2]. This field is increasingly attracting more individuals and businesses that want to invest their money. This thesis research has a deeper focus on stocks investments and portfolio building, once among the various financial markets, the stock market stands out as particularly appealing to many [6, 11].

When discussing the investment topic, it is essential to consider that investment strategies can vary greatly based on the profiles of investors or businesses [1, 14]. Each investor’s profile has unique characteristics, reflecting their preferences, risk tolerance, and decision-making patterns when investing [1, 14]. For beginning investors, these processes are often challenging due to a lack of experience and knowledge in navigating complex market dynamics, highlighting the need for solutions that can simplify decision-making while aligning with their individual goals.

In parallel, the rapid advancement of Artificial Intelligence (AI) has significantly improved the efficiency of diverse sectors, including finance [3, 6, 7, 9, 13, 21]. AI applications such as robo-advisors, algorithmic trading systems, and predictive analytics are increasingly utilized to enhance decision-making processes, optimize portfolio strategies, and mitigate risks in financial markets [8, 9, 13, 16, 20, 21]. By leveraging AI capabilities, financial institutions can process large datasets, identify patterns, and provide actionable insights that were previously inaccessible to investors.

Therefore, in order to optimize the investors’ decision-making processes according to their specific profile, this project explores the role of AI-driven robo-advisors into this investment field. Through a literature review (LR), the research investigates how AI-driven robo-advisors can provide personalized investment advice tailored to the client’s profile while evaluating their impacts over investors’ decisions and portfolio building.

2 PROBLEM STATEMENT

Recent developments and global events have a direct impact on the volatility of financial markets [19]. According to Yasin et al. [19], this volatility complicates the decision-making process for investors, particularly when building portfolios in stock markets. Additionally, this challenge can also be addressed due to a lack of knowledge or experience in this field for beginning investors.

In the digital age, the concept of ’personalization’ has emerged as a critical factor responsible for binding a relationship between institutions and customers [22]. Personalization in finance can enhance trust between investors and financial institutions, encouraging client retention and loyalty.

As a technological solution, the integration of AI in finance has proven effective in enhancing decision-making processes and providing personalized investor experiences. Robo-advisors enable investors to create diversified portfolios tailored to their profiles, budgets, and acceptable risk levels [20].

Given the transformative role of AI in personalizing financial decision-making, this project focuses on exploring the following main research question:

How are AI-driven robo-advisors used to improve personalization and investors’ decision-making in financial markets?

Building on this, this research explores the following sub-research questions to help answer the main research question:

- How does personalization affect the decision-making process of investments?
- What are the impact results of robo-advisors on the personalization and decision-making processes of investors?

3 METHODOLOGY

This study employs a LR to comprehensively analyze existing research and applications of AI in financial markets and how they reflect on customer personalization and decision-making processes. First, this thesis research followed a systematic literature review (SLR) methodology [18], which provided relevant academic articles, book chapters, and case studies that were identified and synthesized

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to develop a structured understanding of current practices and their intersections. However, as developments progressed, some papers were collected from different sources that did not correspond to the SLR, turning this research into a LR.

Papers exploring AI tools, such as robo-advisors, were reviewed to analyze systems for algorithmic trading, risk assessment, portfolio optimization, and predictive analytics, with the aim of improving investors' decisions [8, 9, 13, 16, 20, 21]. Robo-advisors are vital for managing large datasets and offering actionable insights into market trends and investment opportunities [8, 9, 21]. By analyzing these streams of research, it is possible to understand how machine learning enhances decision-making efficiency for investors and financial institutions.

Next, the study explores the impact of personalization on financial industries. Moreover, this research narrows down to how AI applications personalize the customer experience. This section of the research is done by reading and summarizing these topic-related articles, contributing to important insights into how AI algorithms directly affect the relationship between customers and institutions. Such insights include customer preferences, behavior prediction, and personalized interaction impacts.

Building on this, the research explores the role of AI applications in decision-making and personalization to answer the main research question. Therefore, by analyzing, summarizing, and comparing articles, an integration of predictive analytics and decision-making tools from financial markets with personalization is done, which enables a data-driven approach to customer engagement. Such a combination might lead to more precise investment advice and tailored financial solutions for customers.

3.1 Tools and Research Method Used

A systematic literature research or SLR requires a research question, which is answered during the article through reviews and analysis of other pieces of literature [18]. As stated by Wijnhoven and Machado [18], this method needs to document how the processes of collecting, filtering, and analyzing the papers are developed. Therefore, this subsection is responsible for recording the procedure taken to develop this literature review.

After building a research question for the project, the LR consists of some other steps that need to be followed - (1) selecting a literature database, (2) defining search queries, (3) selecting articles, (4) performing analysis and systematic overviews to, finally, (5) reporting the applied search and results [18]. Therefore, this research is developed on the basis of these 5 steps.

First, when defining a literature database, platforms such as Google Scholar[1], Scopus[2], and FindUT[3] were considered. After analyzing each of them, it was decided to use FindUT and Scopus as selected databases, since they may complement each other and lead to an efficient selection of literature in further steps, reducing the probability of limitations. FindUT was used mainly to find reliable papers and Scopus to check the citation analysis and reliability metrics.

[1]https://scholar.google.com/
[2]https://www.scopus.com/
[3]https://ut.on.worldcat.org/discovery?lang=en

During the search for papers, some set of keywords was used to find interesting options related to the topic. The search strings that provided positive options for the project can be found in Fig. 1.

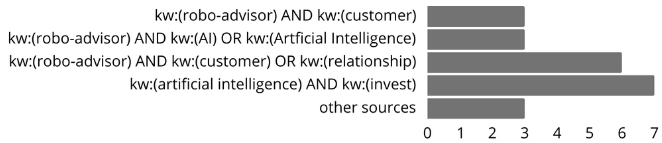

Fig. 1. This graph represents the number of papers found by search strings that were used in this thesis.

Fig. 1 shows that the third and fourth combination of keywords provided the majority of papers utilized in this research. The last category named "other sources" represents the articles that were found from other literature references or from an external source.

The first selection of articles was carefully done depending on the relevance of the papers found and the reliability of the paper according to the journal importance and citations count. Nevertheless, as explained before in this section, some collected articles were gathered by utilizing a different strategy, such as collecting papers from references from other interesting and relevant pieces of research. The list of articles utilized for the development of this LR can be encountered in Table 1 in appendix. Regarding the two last steps, Systematic overviews and Reported Results, these processes were handled on the Result section.

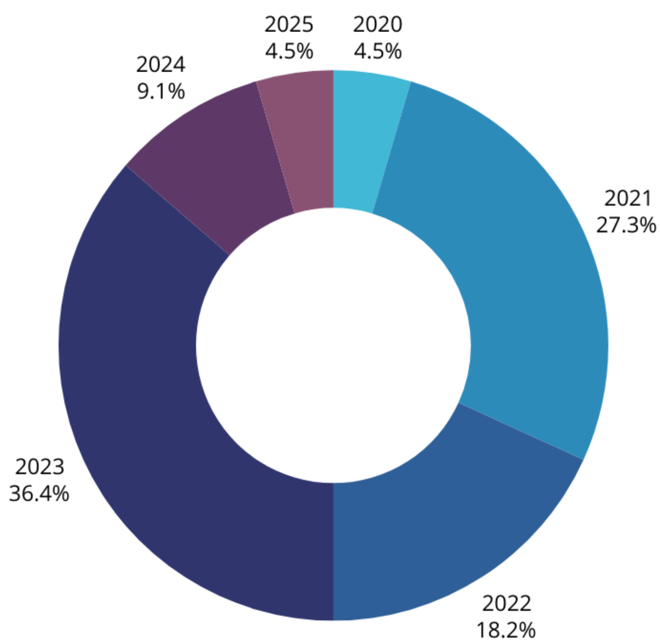

Fig. 2. This graph represents the division of the papers utilized in this thesis by year of publication.

The collected papers were published within the past 5 years. This can be considered as new information, which positively contributes to this thesis project once it focuses on a recent topic that requires technical and up-to-date information.

4 RESULTS AND DISCUSSION

Throughout this literature review, it was possible to obtain valuable information regarding AI and robo-advisors inside finance and on how it affects the customers‘ decision-making processes and the customer experience through the personalization this tool provides.

When collecting papers for this research, as mentioned before, Table 1 in appendix was developed. This table consists of three categories (study name, methodology, and contribution for this project) that explains each reviewed article. This mechanism helped to tailor the research according to the research questions before set.

4.1 AI-Enabled Personalization and Types of AI

In a customer journey perspective, AI has been displaying an important improvement on personalizing customer experience [5]. With a deeper focus on the customer journey phases applied into marketing, Gao and Liu [5] explore the AI-enabled personalization (AIP) concept and conducts its research by exploring literature and observing AIP industry applications in marketing and its interaction with the customers.

By analyzing and complementing collected definitions, Teepapal [17] explained the concept of AI-enabled personalization. According to this article, AIP is a mechanism that aims to comprehend and influence customer behaviors and use it accordingly to tailor the advice for each individual according to their specific needs.

AI can be divided into three main categories - Mechanical AI, Thinking AI, and Feeling AI [7]. These categories, explained by Huang and Rust [7], represent a rising scale of complexity of intelligence as it is displayed on Fig. 3.

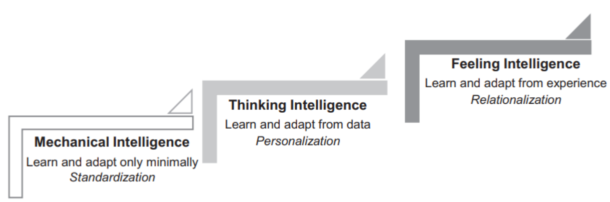

Fig. 3. Representation of AI types. Image retrieved from Huang and Rust [7].

By applying this concept of AI into personalization of investment decisions in finance, the combination of these AI types may improve the customer experience. The introduction of each type of AI in finance is discussed in the following.

- **Mechanical AI:** Mechanical AI represents the simplest form of artificial intelligence, focused on automating repetitive and rule-based tasks without the ability to learn or adapt from data. It operates on pre-programmed logic and fixed rules and works mostly for routine tasks that do not require the AI to “think” [7].
  In the context of investment decisions, Mechanical AI might be the starting point for an investment platform in order to start the automatization process and set some predefined guides for when the client needs help. In this way, it might be useful to start gathering customer data so the Thinking AI can be utilized. It can be used in a chatBot, where it may contain a pre-defined sequence of instructions for messages and displays accordingly to the user input [4]. However, as explained by Galitsky [4], this mechanism is very limited and, therefore, would need to improve the technology behind this intelligence.
- **Thinking AI:** Thinking AI involves cognitive capabilities where the system can analyze data, identify patterns, and make predictions based on historical data. It may use machine learning algorithms and predictive analytics to refine its decision-making over time [7].
  In personalized investment strategies, Thinking AI can customize investment recommendations based on investors’ historical preferences, financial goals, and risk tolerance. For example, robo-advisors use Thinking AI to suggest portfolios tailored to individual investors, considering past behavior and market trends. This personalization can be made with the data gathered from the Mechanical AI.
- **Feeling AI:** The most advanced type which involves emotional intelligence and the ability to assess human emotions and preferences beyond numerical data [7].
  With this approach, it can offer highly personalized investment advice by adjusting strategies not only based on data but also on the emotional comfort level of the investor. For instance, if an investor shows anxiety during volatile markets, the AI might adjust the investment strategy or provide reassurance through emotionally-aware messaging. This could also help to strengthen the retention of the client and improve the B2C relationship.

Gao and Liu [5] define four phases in the customer journey - Personalized Profiling, Personalized Navigation, Personalized Nudging, Personalized Retention - with a focus on marketing and on how to improve the sales of business. The Profiling and Retention phases can be translated for decision-making in the finance field.

Following this, personalized profiling consists in gathering and analyzing data about a customer’s past interactions, purchase and search history, and preferences using AI techniques [5]. This contributes to detailed consumer profiles, predicting future behavior and enabling micro-targeting strategies. Therefore, this type of personalization may help in building the investors profile based on personal details such as risk tolerance and trading history and, consequently, tailoring and targeting the investment advice given by the AI tool and enhancing the decision-making process for investors.

Secondly, the personalized retention phase, when implemented from a marketing perspective, aims on maintaining customer loyalty and engagement after the purchase and on building personalized connections to sustain the relationship and encourage repeat business [5]. However, from this concept, this phase may be used in financial markets in order to automate financial advice and ensure continuous engagement and long-term relationships between investors and financial institutions, for instance.

4.2 Robo-Advisors on Investment Decisions

Robo-advisors, or robo-advisory services, have disrupted traditional human advisory services in banks by offering affordable investment advice that broadens the customer base, particularly to include retail clients [16]. As explained by Scholz and Tertilt [16], these services utilize algorithms that analyze the client's investment profile to recommend a specific investment track. This tool streamlines the onboarding process of new customers and helps determine the client's risk profile, enabling and advising them to make informed investment decisions without the need for direct human interaction.

Robo-advisors impact investor decision-making by mitigating common behavioral biases that often distort human judgment in traditional investment approaches [15]. For instance, robo-advisors help reduce biases like overconfidence, where investors might make overly optimistic predictions about their investments, or herd behavior, where individuals follow the crowd without considering the underlying risk [15]. The algorithms of robo-advisors rely on data-driven insights rather than emotional impulses, leading to more consistent and rational financial advices. This system tends to eliminate the emotions that typically influences human decision-making.

Basic robo-advisors with no AI logic implemented already offer some minimal benefits, however, AI-enhanced robo significantly improves performance on advising investment decisions [3]. According to the obtained results of D'Hondt et al. [3], there is a higher percentage on return for for low-income, low-education, and high-risk-averse investors. It states the efficiency of robo-advisors on markets prediction.

High-risk averse investors gained more from robo-advising, with the median high-risk averse investor showing a return improvement of 0.14%, compared to 3.29% for low-risk averse investors [3]. Low-income investors saw even greater benefits, with a median return spread of 4.13%, compared to 2.76% for high-income investors [3]. From these numbers, it is possible to conclude that it highlights the potential of robo-advisors to assist more financially vulnerable groups.

Moreover, D'Hondt et al. [3] explain the supremacy of robo-advisors over individual and traditional investment decisions in moments of crisis. Following this idea, robo-advisors tend to be more efficient than traditional investment decisions made without the use of AI, as they help mitigate behavioral biases that can negatively influence human decisions, such as overconfidence [15]. Exemplifying this statement with the 2008 financial crises, D'Hondt et al. [3] stated that robo-advisors performed better by holding cash and limiting their exposure to market volatility. However, the authors also mentioned that in normal conditions, robo-advisors continue to perform well.

To compare the robo-advisors' efficiency in moments of crisis, D'Hondt et al. [3] pointed out an example by comparing the robo return with S&P 500 ETF and Belgin ETF during crises. The obtained results presents that robo-advisor's return was 18.32% higher than the S&P 500 ETF and 48.31% higher than the Belgian ETF.

4.3 Personalized Investment Recommendation Process

The process of creating efficient personalized investment recommendations requires a structured approach to data management [9]. The key steps stated by this chapter include data collection, preparation, and curation to ensure high-quality inputs for the recommendation system. The following bullet points explain each step explored by McCreadie et al. [9].

- **Data Collection:** Data must be collected from diverse sources such as financial asset pricing data, customer profiles, and market conditions.
- **Preparation:** It is essential to clean and filter data by removing errors, outliers, and incomplete entries, as poor data quality can affect decision-making accuracy. It also involves anonymizing sensitive data to comply with GDPR and other regulations for user privacy.
- **Curation:** Data curation involves profiling, cleaning, and validating data to ensure it can be effectively used for financial analysis. This involves checking for anomalies, handling missing data, and standardizing formats.

The "Individual Asset Scoring" concept is introduced as a method for ranking financial assets [9]. This scoring system evaluates each asset based on its historical performance, customer profiles, market conditions, and investment horizon [9]. McCreadie et al. [9] explain the key indicators for scoring - asset volatility, returns, and risk factors - and that a higher score indicates a more suitable investment for the customer.

The different strategies of recommendation approaches for personalizing financial asset suggestions developed by McCreadie et al. [9] are explained below.

- **Collaborative Filtering:** This technique relies on historical interactions between users and assets. It identifies similar investment patterns among users to suggest financial products. However, it struggles with data sparsity since many investors may have limited interaction history.
- **User Similarity Models:** These models recommend assets based on user features and historical similarities, using metrics such as cosine similarity. They provide explainable recommendations but can be limited by the availability of comprehensive user data.
- **Key Performance Indicator (KPI) Predictors:** These models predict the profitability of assets using descriptive asset features rather than historical interactions. KPI predictors can recommend new financial products but may lack deep personalization.
- **Hybrid Recommenders:** These combine multiple recommendation strategies, such as merging collaborative filtering with user similarity models. Hybrid recommenders aim to balance accuracy and diversity in asset suggestions but can be complex to implement.
- **Knowledge-Based Recommenders:** These use predefined expert rules to filter and score financial assets based on user preferences and constraints. They are highly explainable but can be limited by static rule sets.
- **Association Rule Mining:** This unsupervised approach identifies frequently co-occurring assets and recommends investments based on historical group patterns. It is useful for market basket analysis but lacks personalization.

Each of these approaches has its advantages and challenges, emphasizing the importance of data quality and diversification of strategies in personalized financial recommendations. When comparing these recommendation approaches, McCreadie et al. [9] concluded that KPI predictors and hybrid models often outperformed collaborative filtering approaches in terms of profitability, though they could be more volatile.

When introducing AI into personalization, genetic algorithms (GA) are an option to tailor financial advice according to individual preferences, risk levels, and market conditions, allowing a broader audience to access professional financial services [10].

The GA concept is inspired by natural selection and evolution theory in order to create optimized investment portfolios that balance risk and return based on multiple personalized constraints [10]. The AI-driven logic process used to build the algorithm that personalizes and tailors the investment advice consists of 6 steps - Initialization, Selection, Crossover, Curation, Mutation, and Iteration - which are explained as follows [10].

- **Initialization:** A set of randomly generated portfolios is created. Each portfolio is scored based on a fitness function considering factors such as risk, return, and diversification.
- **Selection:** Portfolios with higher fitness scores are selected for the next generation.
- **Crossover:** New portfolios are generated by combining features of the top-performing portfolios.
- **Curation:** Data curation involves profiling, cleaning, and validating data to ensure that it can be effectively used for financial analysis. This involves checking for anomalies, handling missing data, and standardizing formats.
- **Mutation:** Random modifications are introduced to maintain diversity and explore new solutions.
- **Iteration:** The process continues through multiple generations until an optimal portfolio is identified.

The advice that used GA resulted in 30% average improvement in portfolio fitness score [10]. This suggests that GA can increase profitability while aligning with the preferences of investors and, consequently, that AI-driven advisor can enhance personalized investment experiences and positive financial returns.

5 CONCLUSION

In conclusion, this study provides insights into the role of AI-driven robo-advisors in enhancing personalization and improving decision-making in financial markets. Through a literature review, it was found that AI technologies (including Mechanical AI, Thinking AI, and Feeling AI) significantly contribute to the personalization of investment strategies, thereby enhancing customer satisfaction. These AI-driven systems tailor investment advice to individual preferences, financial goals, and risk tolerance, which fosters trust and loyalty in financial services. However, ethical concerns, such as data privacy and algorithmic biases, remain important issues that must be addressed to ensure the sustainability and fairness of these systems.

By answering the research questions, this research underscores the potential of AI to enhance financial decision-making, offering a more personalized and data-driven approach that benefits both beginning and experienced investors.

From a scientific perspective, this thesis research contributes to the field of financial technology. It explores the fields of robo-advisors and AI, explaining the functionality, logic behind these tools, and the impacts and implications they have in the real world, such as ethical concerns, data privacy issues, and algorithmic bias. Furthermore, the demographic data collected, including low-income and risk-averse investors, highlights the target population that may benefit most from the implementation of robo-advisors, while also touching on socio-economics.

Addressing the main research question—**"How are AI-driven robo-advisors used to improve personalization and investors' decision-making in financial markets?"**—this study concludes that AI-driven robo-advisors play a transformative role in improving decision-making by providing personalized investment strategies that optimize portfolio management and align with individual investor profiles. By leveraging predictive analytics and real-time adaptability, these systems enhance the efficiency of decision-making, offering a significant improvement in portfolio performance.

The use of AI-driven robo-advisors may have a greater impact on beginner investors by guiding their decision-making processes with personalized recommendations. However, they also demonstrate significant value for experienced investors, enhancing decision-making accuracy and supporting the optimization of complex portfolios. While these findings highlight significant advancements in financial markets, similar approaches could potentially be adapted for other industries where personalization and decision-making are crucial, such as healthcare (e.g., patient treatment plans).

In response to the first sub-research question—**"How does personalization affect the decision-making process of investments?"**—personalization, powered by AI, directly impacts the decision-making process by tailoring investment recommendations based on an investor's historical behavior, financial goals, and emotional responses to market conditions. This leads to more informed and confident decisions, with personalization enhancing customer engagement and satisfaction. By considering unique investor profiles, robo-advisors reduce behavioral biases and improve decision consistency, particularly during volatile market conditions.

Personalization can be considered as one of the causes in achieving an efficient decision-making process for investors. Therefore, by improving the personalized customer experience, it is possible to provide more effective and tailored advice to the client. Moreover, the influence of AI-enabled personalization could extend to other areas, such as retail (e.g., recommending products based on customer history) and marketing, as explored by Huang and Rust [7].

Lastly, robo-advisors have demonstrated significant positive impacts on both personalization and decision-making processes. Studies show that they provide higher returns, particularly for low-income and risk-averse investors. They reduce common behavioral biases and improve decision-making accuracy, leading to better portfolio performance, especially during market crises. Additionally, the use of AI-driven models like genetic algorithms has shown a 30% improvement in portfolio optimization, further highlighting the effectiveness of robo-advisors in providing tailored, data-driven investment advice. These findings directly address the second sub-research question-**"What are the impact results of robo-advisors on the personalization and decision-making processes of investors?"**.

The results analyzed in this thesis research demonstrate the potential of AI-driven systems to enhance decision-making and personalization in financial markets. Several investment fields and other industries may also benefit from this AI tool, which can be investigated in future studies.

5.1 Limitations and Future Research

Although AI offers significant benefits in providing efficient and tailored support for investment decisions, several concerns must be addressed. One key issue is the possibility of biases embedded in AI algorithms, which can lead to misinterpretation of data and result in irrelevant or even harmful recommendations [1, 5, 15]. This risk is heightened if the data collected by robo-advisors is not properly filtered and handled, potentially compromising the service's overall efficiency. Therefore, in order to address this challenge, further research on this field is necessary to avoid or minimize the biases effectively. Such research could focus on widely used robo-advisors in the market and analyze how they address this problem.

Additionally, personalization processes in AI-driven systems may interfere with investors' freedom of choice, raising concerns about privacy limitations [12]. Pizzi et al. [12] highlights that while personalization enhances user experiences, it can also restrict the scope of final returns to clients. Future research in this field could explore smarter approaches to this challenge, such as offering more options to investors while emphasizing that the ultimate decision lies with the customer. This would foster trust and promote autonomy.

Furthermore, the future steps of the impact of AI-driven robo-advisors on the personalization and decision-making processes of investors should also explore regulations that guarantee the safety and privacy of customer data. A deeper research can be developed on how mishandling customer data can lead to privacy concerns. Transparency, fairness, and customer control over data usage must be prioritized to maintain trust and create ethical, customer-centric AI systems [5].

Finally, exploring the integration of robo-advisor mechanisms into investment and banking platforms could prove valuable. Such tools have the potential to enhance the customer experience and strengthen the relationship between financial institutions and their investors. Additionally, conducting deeper research through an expanded review of literature or field studies involving direct customer interaction could provide richer insights.

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6 APPENDIX

During the preparation of this work, I used ChatGPT to correct the grammar, improve the flow of the text, and help with the content organization. After using this tool/service, I thoroughly reviewed and edited the content as needed, taking full responsibility for the final outcome.

Table 1. Literature analysis

Study	**Methodology**	**Contribution for this thesis**
Abdulrasool et al. [1]	Systematic literature review analyzing 156 studies. Used data mapping tools like VosViewer to identify gaps and patterns in behavioral finance literature. Emphasized emotional and cognitive biases affecting decision-making.	Provides insights into individual investors' biases and decision-making, highlighting the need for personalized decision-support systems.
Ashtiani and Raahemi [2]	Systematic review focusing on text mining, sentiment analysis, and machine learning for financial market prediction.	Provides background about financial markets.
D'Hondt et al. [3]	Empirical study that analyzes investor behavior and ML-based portfolio strategies.	Provides some data that confirms the efficiency of the use of AI-driven tools in investment decisions.
Galitsky [4]	Explores discourse analysis for dialogue management, proposing methods to convert paragraphs into hypothetical dialogues. Includes formalized dialogue structures, discourse trees, and evaluations of chatbot performance improvements.	Offers insights into the use of chatbot as one way of using AI-driven tools to personalize the investors decisions and enhance the customer engagement.
Gao and Liu [5]	Paper exploring AI-enabled personalization (AIP) in interactive marketing across the customer journey stages.	Offers the AIP concept and steps of customer journey that can be transcript for personalization in investment decisions. The insights on personalized profiling and retention can guide the AI-driven robo-advisors to improve user experience and adapt to specific customer preferences and needs.
Hernández-Nieves et al. [6]	Describes a platform that integrates machine learning models to provide personalized stock investment recommendations. Uses historical financial data, sentiment analysis, and reinforcement learning to train and validate algorithms.	Highlights the use of diverse machine learning models for dynamic stock recommendations. This provides insights into developing AI-driven robo-advisors that can adapt to changing financial markets while delivering personalized advice based on individual investor profiles.
Huang and Rust [7]	Strategic framework for using AI to engage customers across three AI types: mechanical, thinking, and feeling AI. Explores examples like IBM Watson's application for USAA, leveraging learning, connectivity, and adaptivity.	Highlights how AI can engage users through personalization. Provides insights into integrating AI capabilities for personalized advice, tailored interactions, and user-specific decision support.
Hyun Baek and Kim [8]	Three experimental studies investigating the effects of humanizing AI robo-advisors on investment behaviors.	Highlights the importance of designing humanlike robo-advisors to increase perceived certainty and investment intention. Provides insights into tailoring robo-advisor interfaces to align with individual user motivations for better personalization.
McCreadie et al. [9]	The chapter employs supervised machine learning models (e.g., collaborative filtering and KPI predictors) and hybrid models integrating customer and asset features. It evaluates their performance using data from the National Bank of Greece and the Greek stock market.	This chapter provides a comprehensive evaluation of AI models for financial recommendations, focusing on personalization through customer profiles and historical market data. Insights into model performance and profitability metrics can inform the development of personalized AI-driven robo-advisors.
Meier and Danzinger [10]	Explores genetic algorithms to solve portfolio optimization problems. Simulations optimize multiple financial goals like risk, return, and diversification, incorporating user preferences.	Provides a framework for AI-driven (GA) robo-advisors to offer personalized portfolio strategies, enabling dynamic adjustments based on user-specific financial goals, risk tolerance, and market changes. This enhances personalization and adaptive investment solutions.

Pandit et al. [11]	The chapter employs reinforcement learning models to optimize trading strategies. It focuses on stock markets concepts.	Highlights the potential of stock markets as the focus within the financial market domain for this research.
Pizzi et al. [12]	Experimental studies with 400 participants, investigating the effects of chatbot anthropomorphism.	Explores how personalization can be a limitation for this research, once it may interfere in investors' freedom of choice.
Reddy and Nagarjuna [13]	Employs machine learning algorithms to analyze historical financial data in order to develop investment portfolios. Evaluates model performance using predictive accuracy metrics, such as Sharpe Ratio and cumulative returns.	Provides insights into dynamic portfolio management and AI-driven tools impact on investment decisions.
Schoar and Sun [14]	Randomized controlled trial (RCT) examining how investors deal with different types of advice.	Highlights the importance of investors' personal characteristics in the analysis when advising them.
Scholz et al. [15]	Analysis of behavioral biases in robo-advisors' processes and impact on investment decisions.	Offers insights into how biases can be reduced with the use of robo-advisors. Also, provides information for the limitation section (biases might persist in AI-driven investment systems).
Scholz and Tertilt [16]	Analysis of the history, market dynamics, and operational methodologies of robo-advisors, focusing on financial advisory services.	Explores how robo-advisors enhance accessibility and efficiency in investment decisions.
Teepapal [17]	Quantitative survey-based study using the S-O-R model.	Provides the AI-enabled personalization (AIP) definition and how it influences trust and privacy concerns.
Wijnhoven and Machado [18]	Descriptive methodology focusing on systematic and non-systematic literature search and academic paper writing.	Provides a clear and descriptive tutorial on building a SLR or LR.
Yasin et al. [19]	Case study focusing on portfolio optimization.	Provides information about financial markets and helps to build the problem statement of this thesis by addressing the issues this field faces, such as volatility.
Yeh et al. [20]	Quantitative study about robo-advisors using the UTAUT framework with data from questionnaires, analyzed by variables such as experience and investment-to-income ratio.	Explores user attitudes and behavioral intentions toward robo-advisors, and helps to define how robo-advisors impact the decision-making processes of investors
Zhang et al. [21]	Study that analyzes ETF funds using portfolio return formula and random forest model to assess the impact of robo-advisors on returns.	Highlights the potential of robo-advisors in improving portfolio returns and decision-making processes of investors. It focus on risk attributes and optimizing personalization in AI-driven investment strategies.
Zhang et al. [22]	Proposes the Inductive Contextual Personalization (ICP) framework to capture contextual relations.	Introduces the personalization concept which is explored in this thesis research.