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Investor Behavior in the Age of AI

A Dual-Theoretical Examination of Risk Tolerance and Biases in Investment Decision-Making

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Abstract: Investor behavior is rapidly changing as a result of artificial intelligence's (AI) quick integration into financial markets. The impact of AI investment tools on investors' risk tolerance and biases in decision-making is examined in this thesis. These tools include sentiment analysis platforms, algorithmic trading systems, and robo-advisors. The study compiles the scholarly literature that investigates this crucial intersection through a systematic literature review and bibliometric analysis. Key findings show a notable increase in scholarly interest since 2016. There is evidence that AI tools can reduce behavioral biases like the disposition effect by encouraging disciplined investment strategies. But interactions with biases like herd behavior and overconfidence are complicated and can result in new kinds of cognitive traps or an over-reliance on automated systems. The impact of AI differs depending on the kind of tool. Several tool types and investor segments are affected by AI in different ways. The study clarifies the cognitive and psychological processes by which AI influences intuitive (System 1) and deliberative (System 2) thinking and reframes investor perceptions of gains, losses, and risk by combining these empirical observations with Dual Process Theory and Prospect Theory. The study emphasizes the necessity for frameworks that promote informed AI adoption and support prudent financial decision-making in an increasingly AI-augmented investment environment, underscoring the significant ramifications for investors, financial advisors, technology developers, and regulators. By advancing our knowledge of the changing human-AI relationship in finance, this study opens the door to more efficient and behaviorally conscious financial technologies.

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Contents

I. Description of Appendix Figures

This chapter lists and discusses the figures and appendices that can be found in chapter **XI. Appendix**.

Figure 1 shows a screenshot of the different searches that were made with the use of Scopus, while Figure 2 shows the extraction filters that were chosen to constitute the database and perform the quantitative analysis of the search results.

Figure 3 to 29 show a series of three charts that were chosen from the quantitative analysis (available in the Excel file "Consolidated Data"), based on the following criteria:

Three charts were selected out of all the charts made during the quantitative analysis for each of the Scopus search queries, to give the reader a compact yet multidimensional portrait of each thematic corpus, mirroring the key evaluation criteria used in modern bibliometric reviews. The first chart, Documents (or Publications) by Year, maps the temporal evolution of scholarship. This time-series view lets the reader instantly see whether a topic is emerging, maturing, or stagnating. For example, the pronounced inflection after 2016 across most sheets aligns neatly with the commercial rollout of robo-advisors and large-language-model (LLMs) breakthroughs, validating the timeliness of the research and setting a chronological backdrop for subsequent discussion.

The second chart, Affiliation Country share, shifts the focus from *when* to *who*. Geographic provenance signals where intellectual leadership and practical experimentation are concentrated. By revealing, for instance, that the United States and China dominate AI-finance research while Europe leads inertia-bias studies under stricter default regulations, the chart underscores the contextual factors (market structure, regulatory regimes, data availability) that shape findings. This global snapshot also reassures reviewers that the evidence base is not limited geographically, enhancing external validity and stressing the thesis's claim to international relevance.

Finally, the Citations per Year trend provides the impact dimension that raw publication counts cannot. A rising citation curve demonstrates that the literature is not only proliferating but also resonating with scholars, an essential marker of intellectual traction and theoretical significance. By juxtaposing citation momentum with output volume, you help readers distinguish between topics that are merely popular and those that are substantively influential. Taken together, the three visuals weave a concise narrative of momentum, provenance, and influence, giving appendix readers the "who-when-how important" story at a glance and freeing the main text to delve into deeper thematic analysis.

The only other figures/images in this research paper are the ones found in the **V. Findings/Results** chapter. For each of the search queries made on Scopus, a screenshot was made of the consolidated data (available in the Excel file "Consolidated Data"), and inserted in the results chapter instead of the appendix, which seemed more relevant to the author.

II. Introduction

2.1 Background

The rapid integration of artificial intelligence (AI) is a major factor driving the significant transformation of the financial services sector. Machine learning, natural language processing, and advanced data analytics are just a few of the AI technologies that are changing how financial institutions function, how investment products are created, and, most importantly, how investors engage with markets (D'Acunto et al., 2019; Eichler & Schwab, 2024). AI's emergence in financial services represents a paradigm shift rather than a small adjustment, providing previously unheard-of abilities in data processing, pattern recognition, and automated decision-making (Beketov et al., 2018). AI is democratizing access to financial tools and information while also bringing new complexities and challenges, such as algorithmic trading systems that execute transactions at microsecond speeds (Arumugam, 2023; Boehmer, Fong, & Wu, 2021) and robo-advisors that offer individualized investment management to a wide range of retail audiences (Jung et al., 2018; Back et al., 2023).

This technological revolution is taking place in the context of changing investor behavior in the digital era. Individual investors now have more freedom and access to financial information than ever before thanks to the growth of social media, mobile trading apps, and online brokerage platforms. But investors are also subjected to a large amount of information, quick market swings, and new psychological effects in this digital world (Bhutto et al., 2025; Kumar & Prince, 2023). Traditional behavioral biases like herd behavior fueled by online communities or overconfidence resulting from easily accessible information can be exacerbated by the convenience and speed of digital interactions (Huang & Chen, 2018). Because AI tools are becoming more and more integrated into the investment decision-making process, it is crucial to understand investor behavior in this digital environment. These tools may mediate or alter these innate human tendencies (Lopez, 2022; Dietvorst, Simmons, & Massey, 2015).

The combination of AI development and the digitalization of investment processes requires a more thorough investigation of the ways in which these factors interact to influence investor decisions, risk assessments, and cognitive error vulnerability. Academics and financial professionals are becoming more interested in how AI tools affect the psychological aspects of investing, especially in terms of risk tolerance and decision-making biases, as they provide a more advanced and personalized financial advice.

2.2 Research Problem and Interest of the Study

Both significant opportunities and difficult challenges are presented by the increasing use of AI tools in the financial ecosystem. Even though these technologies have the potential to improve efficiency, democratize access to investment advice, and even mitigate some human errors (Back et al., 2023; D'Acunto et al., 2019), it is still necessary to conduct further research to determine exactly how they affect the psychological foundations of investor decision-making, particularly related to risk tolerance and behavioral biases. This thesis's main research problem is the knowledge gap regarding how investors' cognitive and emotional reactions are influenced by and shaped by their interactions with AI investment tools. The effects of biases like status quo bias, herd behavior, and overconfidence on investment outcomes have been well-documented by traditional behavioral finance (Bouteska et al., 2023; Bhutto et al., 2025; Samuelson & Zeckhauser, 1988). Likewise, it has been acknowledged that risk tolerance is not a constant characteristic but rather a dynamic and context-dependent one (Kahneman & Tversky, 1979; Guiso, Sapienza, & Zingales, 2018). But when AI becomes an active participant in the investment process, it adds a new factor whose impact on these widely known behavioral constructs is still unclear.

The critical need to understand how AI affects risk tolerance and behavioral biases is what drew this study's attention for a number of important reasons. First off, it is crucial to determine whether AI-powered platforms are actually encouraging more logical decision-making or unintentionally introducing new types of bias or over-reliance as retail and institutional investors depend more and more on them for advice, portfolio management, and trade execution (Jung et al., 2018; Arumugam, 2023; Dietvorst, Simmons, & Massey, 2015; Hildebrand & Bergner, 2021). Second, if AI tools are not carefully designed and implemented, they may reinforce or create certain biases (Scholz, Tertilt, & Vorsteher, 2021), which could have unexpected effects on investors and market stability. Third, in order to develop frameworks and tools that facilitate careful financial decision-making in an AI-augmented future, financial educators, regulators, and technology developers must have a thorough understanding of this interaction. This is an intriguing and relevant field of study because AI has the potential to either serve as a remedy for human biases or as a trigger for brand-new psychological traps. Therefore, this study aims to clarify the complex relationship between AI technology and investor psychology, with an emphasis on how AI investment tools influence investors' ability to assess and manage risk as well as their vulnerability to common decision-making biases.

2.3 Research Question and Objectives

To address the identified research problem, this thesis is guided by a central research question that seeks to understand the complex relationship between AI investment technologies and investor psychology. The primary research question is:

How do AI investment tools influence investors' risk tolerance and decision-making biases?

This predominant question aims to explore the numerous impacts of AI on two critical dimensions of investor behavior: their willingness and capacity to undertake financial risk, and their susceptibility to systematic cognitive and emotional errors that can lead to suboptimal investment outcomes. To systematically investigate this question, the study determined a set of specific objectives, which are divided into main and secondary objectives as follows:

Main Objectives:

1. To carefully examine how much investors' stated and disclosed risk tolerance is influenced by AI investment tools (such as robo-advisors, algorithmic trading platforms, and sentiment analysis tools). This involves determining whether AI tools create new patterns of risk perception and behavior or result in more consistent, logical risk-taking (Guiso, Sapienza, & Zingales, 2018; Hoffmann, Post, & Pennings, 2015).
2. To look into the ways that AI investment tools interact with and possibly change common investor behavioral biases, such as status quo bias, herd behavior, and overconfidence (Back et al., 2023; Bhutto et al., 2025; Bouteska et al., 2023; Samuelson & Zeckhauser, 1988).
3. To interpret and clarify the observed effects of AI tools on investor risk tolerance and decision-making biases by applying well-established theoretical frameworks from behavioral finance, particularly Dual Process Theory (Kahneman, 2011; Renevier, 2024) and Prospect Theory (Kahneman & Tversky, 1979).

Secondary Objectives:

1. To identify current knowledge and research gaps, the literature on behavioral finance, risk tolerance, the use of important AI investment technologies, and earlier studies on how these technologies interact with investor behavior will be reviewed and synthesized (Darskuviene & Lisauskiene, 2021; Lopez, 2022).
2. To investigate how different kinds of AI tools (such as sentiment analysis data versus automated advice from robo-advisors) affect particular investor biases and risk tolerance factors (D'Acunto et al., 2019; Fatouros et al., 2023).
3. To consider the role of investor characteristics (such as financial literacy, age, and prior investment experience) as potential moderators in the relationship between AI tool usage and behavioral outcomes (Kumar & Prince, 2023; Lisauskienė et al., 2024).

4. To go through the findings' practical implications for financial advisors, technology developers, retail and institutional investors, and regulatory agencies looking to create a more resilient and educated investing environment in the era of artificial intelligence.

By pursuing these objectives, this thesis aims to provide a comprehensive understanding of the evolving landscape of investor behavior as it is increasingly influenced by artificial intelligence, contributing valuable insights to both academic theory and financial practice.

2.4 Significance of the Study

This study has significant implications for a number of fields, adding to the body of knowledge regarding behavioral finance and the role of technology in investing. It also provides useful information for a wide range of stakeholders, including institutional and retail investors, financial advisors, technology developers, and regulatory agencies. The study's relevance comes from its timely examination of the rapidly evolving relationship between artificial intelligence and human financial decision-making.

Theoretical Contributions:

This thesis mainly advances behavioral finance by applying its concepts to AI investment environments. Human biases and nuances of risk perception have been thoroughly recognized and examined by behavioral finance (Thaler, 2017; Kahneman & Tversky, 1979), but research on how these mental processes interact with advanced AI tools is still in the early stages. The goal of this study is to increase theoretical knowledge of how AI technologies can either mitigate or amplify known behavioral biases (Back et al., 2023; Dietvorst, Simmons, & Massey, 2015). Applying Prospect Theory (Kahneman & Tversky, 1979) and Dual Process Theory (Kahneman, 2011) to examine AI's impact will provide a more detailed understanding of the cognitive and affective processes involved when investors interact with these emerging technologies. By doing this, current behavioral models can be improved to better take into consideration the loop of interactions between humans and AI in financial decision-making.

The study also adds to the body of knowledge on the adoption of technology and how it affects financial markets. The study will shed light on the precise ways that technology is changing investor psychology and market dynamics by analyzing the distinct ways that various AI tools, such as robo-advisors, algorithmic trading, and sentiment analysis, affect investor behavior (Arumugam, 2023; Fatouros et al., 2023; D'Acunto et al., 2019). Given the speed at which AI is developing and its growing integration into every aspect of the financial sector, this is especially pertinent (Eichler & Schwab, 2024).

Practical Insights for Investors:

This study provides insightful information about how AI tools may be affecting the investment decisions, risk tolerance, and the exposure to bias of retail investors. Understanding these dynamics can help individual investors adopt and use AI-powered platforms more wisely, identifying potential risks (such as automation bias or over-reliance) and more successfully utilizing the advantages (such as bias mitigation or disciplined rebalancing) (Shukla & Shukla, 2023). By improving financial literacy about AI tools, the findings can help retail investors make more informed and confident decisions when navigating the digital investment landscape.

The study gives institutional investors a better idea of how AI technologies are influencing market behavior and possibly their own decision-making processes. This includes their own algorithmic trading systems and those of other market participants. To ensure that human oversight continues to be effective in an increasingly automated environment, greater trading strategies, risk management frameworks, and internal training programs can be designed with insights into the behavioral impact of AI (Boehmer, Fong, & Wu, 2021; Kirilenko et al., 2017).

Implications for Financial Advisors and Technology Developers:

This research can help financial advisors better understand how their clients may be using and being impacted by different AI tools. Stronger advisor-client relationships and better client outcomes may result from advisors using this knowledge to effectively incorporate AI insights into their practice, educate clients on the proper use of AI technologies, and customize their advice. The study might also point out areas where, despite an AI-dominated environment, human advisory skills are still crucial.

The results can be used by FinTech firms and technology developers to create AI investment tools that are more morally and practically sound. Instead of unintentionally reinforcing or creating new behavioral biases, platforms that truly support rational decision-making and mitigate them can be created by taking into account the psychological effects of various design decisions (such as anthropomorphic features and algorithm transparency) (Back et al., 2023; Hildebrand & Bergner, 2021). Creating AI systems that encourage users to use System 2 thinking and offer concise, accessible justifications for their suggestions is part of this.

Relevance for Regulators and Policymakers:

Lastly, regulators and policymakers are encouraged to take note of the study's findings. Understanding AI's behavioral effects is essential as it becomes more integrated into financial markets in order to create suitable regulatory frameworks that guarantee investor protection, market integrity, and financial stability (Tiffin, 2019). Policies related to disclosure requirements for AI advice, the transparency of AI algorithms, and steps to reduce systemic risks that could result from the widespread use of specific AI techniques can all be influenced by the research (Zhang & Zhang, 2024).

In essence, the significance of this study lies in its potential to reveal the complex, evolving relationship between human investors and artificial intelligence, providing a foundation for more informed, effective, and responsible engagement with AI in the world of finance.

2.5 Structure of the research

To methodically address the research question and objectives, this thesis is divided into multiple chapters, each of which focuses on a distinct area of the study. The structure is intended to logically lead the reader from the problem statement and underlying ideas through the literature review, methodology, results, discussion, and closing thoughts.

A brief synopsis of the research, a plan of the document, and a list of illustrative materials are among the standard preliminary materials for the thesis that are provided in the first chapters.

Chapter II: Introduction (the current chapter) provides background information for the study. It starts by providing an overview of the origins of artificial intelligence in financial services as well as the circumstances surrounding investor behavior in the digital era. The research problem is then defined, the main research question and particular goals are stated, and the study's importance for different stakeholders is covered. This summary of the thesis structure is given at the end.

Chapter III: Literature Review examines the existing body of knowledge pertinent to the research. It covers four main topics: It begins by examining the fundamentals of behavioral finance and the main investor biases, such as herd behavior, overconfidence, and status quo bias, as well as how these affect the results of investments. Second, it looks at how risk tolerance is used in investment decision-making, including its classical definition, behavioral insights into how dynamic it is, how it is measured, and how AI tools affect it. Third, it describes the theoretical frameworks, Dual Process Theory and Prospect Theory, that support the research and their implications for understanding the impact of AI. Fourth, it gives a summary of AI investment technologies, such as sentiment analysis tools, algorithmic trading, and robo-advisors.

Chapter IV: Methodology discusses the research strategy used in the study. It describes the research design and methodological decisions, such as the database selection, screening processes, data export and management, bibliometric research search strategy, and analysis tool selection. It also recognizes the limitations of the selected methodology and discusses the ethical issues relevant to the study.

Chapter V: Findings/Results presents the empirical outcomes of the research. This chapter systematically reports the data collected and analyzed according to the methodology described in the preceding chapter.

Chapter VI: Discussion interprets the key findings presented in Chapter V. It links the empirical results back to the research question and objectives. A significant portion of this chapter is dedicated to integrating the findings with the theoretical frameworks of Dual Process Theory and Prospect Theory, explaining how these theories illuminate the results. The chapter also elaborates on the implications of the findings for both practice (financial advisors, technology developers, regulators) and theory.

Chapter VII: Conclusion provides a comprehensive summary of the research. It recaps the aims, methodology, and major findings of the study. It highlights the contributions to knowledge, both theoretical and practical, coming from the research. The chapter concludes with final remarks that link the research back to the broader context of AI and investor behavior, offering a forward-looking perspective.

Chapter VIII: Limitations of the Study provides an open discussion of the limitations and restrictions that were faced during the research process, which could have an impact on how the results are interpreted or how broadly they can be applied. This covers scope constraints, methodological limitations, and any other elements that should be taken into account.

Chapter IX: Recommendations for Future Research expands on the results and constraints of the present investigation to propose directions for further academic research. It highlights open-ended questions and developing fields in the fields of artificial intelligence and investor behavior that demand more research.

Chapter X: References lists all the academic sources, publications, and other materials cited throughout the thesis, adhering to the APA citation style.

Chapter XI: Appendix includes supplementary materials that support the research but are not integral to the main body of the thesis, such as extended data tables, or research and extraction filtering.

III. Literature Review

3.1 Behavioral Finance and Investor Biases

Overview of behavioral finance principles

As a fundamental change in the understanding of financial markets, behavioral finance challenges the conventional viewpoint that depends only on effective information use and logical decision-making. Fundamentally, behavioral finance recognizes that investors are people with emotions and cognitive processes that go beyond simple economic reasoning when making decisions (Bhutto et al., 2025). This area of study developed in response to financial market anomalies that conventional theories based on rational expectations and the Efficient Market Hypothesis were unable to sufficiently explain. Numerous systematic biases and heuristics have been discovered in recent decades, demonstrating how human psychology can predictably influence investor behavior and asset prices (Thaler, 2017).

The main idea behind behavioral finance is that investor decision-making is consistently impacted by psychological biases and cognitive limitations. The impact of these non-financial factors on stock prices and market volatility has been well-documented by research. For instance, speculative bubbles, excessive trading, and the equity premium puzzle have all been connected to herding behavior, overconfidence, and loss aversion. According to Almansour and Arabyat (2017), psychological elements like fear and euphoria can influence investment decisions, even for professionals. Ahmed et al. (2022) have discovered that changes in investor sentiment and socio-political factors can have a significant impact on portfolio performance. This suggests that factors other than traditional financial metrics influence the results of investments. Behavioral finance acknowledges that emotions and cognitive distortions are major contributors to market inefficiencies, in contrast to traditional finance, which views information symmetry and rational agents as the main forces behind market movements. This realization has major implications since it suggests that patterns in investor psychology and collective behavior may cause asset prices to diverge from fundamental values in addition to information asymmetries or risk premiums. Overly optimistic or pessimistic market sentiment can result in mispricing that would not be predicted by a strictly rational model.

For instance, Internet companies' stock prices skyrocketed to levels well above what their earnings and growth prospects could support during the dot-com bubble of the late 1990s. Behavioral finance provided insights through ideas like herding and overconfidence, while traditional finance found it difficult to explain this ongoing overvaluation. The market frenzy caused investors to follow one another's lead (herding), and many of them overestimated their own abilities to choose the "next big thing" in technology (overconfidence). Before reality finally stepped in and the bubble burst, these psychological factors created a collective enthusiasm that drove prices above reasonable levels. This historical example shows how behavioral factors can lead to long-lasting, substantial market distortions. In a similar way, extreme volatility and price deviations from fundamentals were caused by investor psychology, fear of missing out, and social media-induced herd behavior in the 2017–2018 Bitcoin boom and the early 2021 GameStop meme stock incident. Understanding the behavioral foundations in each instance, such as online herding in the GameStop saga and FOMO, helps explain results that conventional models would consider anomalies.

Numerous factors, such as individual personality traits, risk perceptions, social influences, and different emotional biases, have been identified by the behavioral finance literature as influencing investment decisions (Ahmed et al., 2022; Lather et al., 2020; Hossain & Siddiqua, 2022; Pa et al., 2022, as cited in Bhutto et al., 2025). These elements frequently result in less-than-ideal investment decisions that diverge from what traditional risk-return optimization models would have predicted. For example, investors often display loss aversion because they feel the pain of losses more strongly than the joy of gains. As a result, they either avoid selling losing investments or expect extremely high potential gains to offset a potential loss. This adds to the previously mentioned disposition effect and portfolio inertia. Furthermore, according to Prospect Theory (Kahneman & Tversky, 1979), many investors exhibit risk-aversion in gains and risk-seeking in losses. This leads to actions such as favoring a certain but smaller gain over a riskier larger gain and betting on a larger loss in order to avoid a sure-small loss. Additionally, behavioral studies have demonstrated that investors' perceptions of risk are dynamic and context-dependent, subject to change in response to recent market performance or the framing of options. For instance, investors may overestimate risk and become overly conservative following a market crash, while they may underestimate risk (becoming overconfident) following periods of market stability (a form of the recency effect). Despite writing from a classical perspective on dividends and returns, Fama and French (1988) alluded to time-varying risk premiums that could also be interpreted through a behavioral lens. This is because when market sentiment changes, so do the required returns, which in turn affects prices. Menon et al. 2023, as cited in Bhutto et al., 2025) and others offer more direct behavioral evidence, demonstrating that traits such as personality (e.g., neuroticism or extraversion) and financial literacy can affect an investor's exposure to biases or risk perception. While a more nervous person may be more prone to status quo bias or overly cautious behavior, an aggressive personality may trade more frequently (possibly because of overconfidence). According to Lather et al. (2020), who study how personality affects biases, qualities like conscientiousness are associated with a decreased tendency for impulsive biases. Investment behavior is a complex interaction between human psychology and logical calculation, as these interdisciplinary findings (which mix psychology and finance) highlight.

By adding psychological realism to economic models, behavioral finance has completely changed how we think about financial markets. This field offers a more thorough framework for examining market behavior by recognizing that investors are susceptible to emotional influences, heuristics, and cognitive limitations. Anomalies like asset price bubbles, excessive volatility, or momentum effects are now examined as the results of human behavior in a market environment rather than being written off as random noise. This viewpoint has produced more sophisticated asset pricing models (such as those that incorporate sentiment or bounded rationality) as well as useful applications like advisor strategies to mitigate client biases and behavioral portfolio construction. In addition to helping to explain market anomalies, behavioral finance concepts provide guidance on how investors can enhance their decision-making by identifying and reducing their own biases. For example, an advanced investor may purposefully look for opposing viewpoints before making a trade, aware of confirmation bias, the tendency to seek information that supports one's preconceived notions. An investor may wonder if a hot stock tip is a good idea or just interesting because it's in the news after learning about availability bias, which is the tendency to overvalue information that is easily remembered. Because an investor who is aware of these typical pitfalls is better equipped to steer clear of them or implement safeguards (such as checklists or robo-advisory tools) to mitigate them, behavioral finance therefore provides awareness to advisors and investors. This basic knowledge that markets are influenced by human psychology just as much as by economic principles will be crucial background information as we examine specific biases in the sections that follow. It serves as a reminder that market results frequently mirror the collective behavior of people, which can be naturally irrational. As such, any examination of investor behavior in the era of artificial intelligence must take these psychological tendencies into account.

Key Biases Explored: Overconfidence

One of the most common and significant cognitive biases influencing investment decision-making is overconfidence. Investors who overestimate their knowledge, expertise, or the accuracy of the information they possess exhibit this bias by becoming unduly confident in their forecasts or skills. Because they think they can consistently pick winners or time the market, overconfident investors frequently trade more frequently than is wise and place undiversified bets. Even during times of great uncertainty, like the COVID-19 pandemic, investor overconfidence persisted in developed markets, including the U.S., from 2016 to 2021, according to research by Bouteska et al. (2023). In their study, they explain how overconfident investors frequently trade excessively, chasing recent gains because they think their success is the result of skill rather than luck. Even as markets moved wildly in 2020, this pattern was visible; despite the high volatility, some investors took rebounds as confirmation of their skill and increased their trading. Due to transaction costs and bad timing (buying high, selling low), such behavior usually results in lower net returns. This finding is in line with previous classic studies (Barber & Odean, 2000) and is supported by this recent data from Bouteska et al. (2023).

Numerous investor demographics have been the subject of research on the factors that contribute to overconfidence bias. According to Bouteska et al. (2023), overconfidence endures even in developed markets with an abundance of information, such as the United States. Other studies have connected overconfidence to variables like gender and experience. For instance, a number of studies have discovered that, on average, male investors trade more frequently than female investors, a trend that has been linked to men's higher levels of overconfidence in financial matters. Barber and Odean (2001) famously documented this, and more recent observations have shown that it is still true (Kumar & Prince, 2023). Age and market cycle can also be factors. For example, investors who started their investments during an extended bull market might start to feel in control or skilled, only to be taken aback when a bear market hits. According to Kumar and Prince's (2023) systematic mapping of the literature, overconfidence is a global phenomenon that impacts investors in both developed and emerging markets. It is still a crucial area for additional research, as it may interact with access to social trading platforms or artificial intelligence tools. Research has shown that new investor groups in emerging markets, like Gen Z, who frequently trade through mobile apps, exhibit overconfidence driven by social media and online forums. As demonstrated by some penny stocks or cryptocurrencies, this can result in speculative frenzy, where young investors overestimate their capacity to outsmart the market and trade quickly based on trending information.

In general, under-diversification and market timing errors are caused by overconfidence bias. Investors who are overconfident may focus their portfolio on a small number of stocks (typically well-known or local businesses, or popular industries like technology), thinking they have better knowledge of them. Additionally, they might disregard index or benchmark investing because they believe active trading will produce higher returns. However, the opposite is consistently demonstrated by empirical data: people who trade more and deviate from diversified portfolios typically perform worse. This is supported by Bouteska et al. (2023), who demonstrate that excessive trading between 2016 and 2021 was linked to lower returns, even though some overconfident traders persisted in trading despite unfavorable performance feedback. Overconfidence seems to be self-sustaining; short-term successes, even if they are the result of chance, serve to reinforce the bias, while failures are frequently attributed to bad luck or outside circumstances rather than an issue in the decision-making process. Self-attribution bias, in which investors blame outside noise for losing trades and their own skill for winning ones, exacerbates this bias even more. Such thinking keeps overconfidence alive by preventing learning and error correction.

For instance, an overconfident day trader may decide they have a unique talent for stock selection after making money in a rising market. After that, they might double down by using leverage or increasing the frequency of trades, only to suffer significant losses if the market trend turns around or a few of their picks don't work out. However, instead of reconsidering their approach, they may attribute the losses to "unprecedented events" and carry on with their trading. This tendency was demonstrated during the retail trading boom of late 2020–early 2021, when a large number of new investors increased their speculative bets after feeling encouraged by rapid gains in stocks and options. According to brokerage data, accounts that engaged in the most aggressive option trading frequently experienced the worst drawdowns during periods of increased volatility (such as the February 2021 meme stock crash). As a sign of overconfidence, the investors had lost sight of their own limitations.

Overconfidence must be addressed for the benefit of both people and the market at large. In order to combat the tendency to trade impulsively, tools such as robo-advisors can enforce discipline on an individual basis. For example, they can encourage investors to diversify or establish predetermined guidelines for rebalancing. Certain robo-advisors serve as a check on overconfident decisions by specifically alerting users if they attempt to diverge substantially from suggested portfolios. Overconfidence can lead to excessive volatility and mispricing at the market level. Overconfidence among many investors can cause trading volumes to soar (as in bubbles), prices to overshoot fundamental values, and, ironically, liquidity to thin out at extremes. Policymakers and logical investors can react more appropriately (e.g., by tightening margin requirements or taking contrary positions) if they recognize that psychological bias, rather than new information, drives such periods. In conclusion, overconfidence is still a major behavioral bias in the era of artificial intelligence. Despite the availability of more tools and information, human investors may still overestimate their own skills. Improving investment results requires acknowledging this bias and putting protections in place (like algorithmic support or reflective decision-making techniques). Education about overconfidence and its risks has become even more important as markets have become more accessible (zero-commission trading, etc.), in order to keep retail investors from taking on too much risk and damaging their financial well-being.

Key Biases Explored: Herd Behavior

Investors' tendency to follow the actions of others rather than form their own opinions based on their own data or analysis is known as herd behavior, and it is a significant psychological bias in investment decision-making. The literature on behavioral finance has examined this phenomenon in great detail. Important information about how herding affects investment decisions and interacts with other psychological factors is provided by Bhutto et al. (2025). According to their research, herding behavior significantly influences people's investment choices in a positive way, indicating that this bias significantly influences market dynamics. In other words, a trend that is largely independent of fundamental value can become self-reinforcing when a large number of investors move in the same direction (purchasing or selling an asset). Herding can happen for emotional (fear of missing out, or the ease of following others' lead) or rational (information cascades, where investors believe others have superior knowledge) reasons. Whatever the reason, the result is that when "the herd" moves in or out, asset prices may deviate from their intrinsic values.

Herding influences decisions in a variety of intricate ways. According to Bhutto et al. (2025), the relationship between herding and decision-making is influenced by risk perception. Investors are more inclined to purchase an asset when they see a large number of other people purchasing it. This is because they may believe that the asset is less risky ("if everyone is buying, it must be safe or a good bet"). On the other hand, witnessing others sell in a panic can increase a person's risk assessment of owning that asset, leading them to sell as well. This mediation effect demonstrates how social factors can skew people's perceptions of risk and possibly result in group market decisions that aren't supported by basic facts. Bhutto et al. demonstrated, using structural equation modeling, that the influence of herding on investment choices was partially mediated through altered risk perceptions and even affected corporate decisions, such as dividend policy (the latter implying that common investor biases can influence company behaviors, which in turn feedback into investor decisions, an interesting relationship between markets and corporate management). Their results support the idea that psychological biases are interconnected, with herding working in combination with perceptions of risk, fear, and greed rather than independently.

For instance, thousands of retail investors bought shares of GameStop during the early 2021 stock craze largely based on social media hype and other investors' observed behavior rather than a fundamental analysis of the company's worth. Reddit forums and Twitter helped amplify this collective behavior, which caused GameStop's share price to soar to unprecedented heights that were beyond the realm of conventional valuation techniques. When the price finally crashed, many latecomers who joined the buying herd lost a lot of money, highlighting the possible drawbacks of herd-following behavior. In this instance, herd behavior was driven by psychology (the thrill of joining a collective “revolution” against hedge funds, fear of missing out on enormous gains) as well as informational cascades (observing others make money attracts new entrants). Interestingly, some investors joined the wave despite knowing the fundamentals were weak, demonstrating how strong the herd behavior can be and how it can override independent analysis.

Herding behavior complicates investor decision-making by interacting with other psychological elements. A feedback loop where investor psychology influences corporate actions that then reinforce specific investor behaviors is suggested by Bhutto et al.'s (2025) findings that behavioral factors, such as herding, influence firms' dividend policies, which in turn affect investors' decisions. Their research also showed that herding behavior, which can increase transaction frequency and shorten investment horizons (investors trade more and think shorter term when they herd), is especially visible when risk perception is higher than usual. This finding supports the notion that, in unpredictable times, investors look for "safety in numbers." Herding frequently appears as correlated panic selling in volatile or bear markets, while bandwagon buying occurs in ebullient bull markets. Both can increase volatility: in bubbles, herding causes the bubble to expand (everyone swarming in), and in crises, herding speeds up price drops (everyone running for the exits at once). Even though individual investors may typically be rational in isolation, these behaviors can result in collective irrationality, which challenges the efficient market hypothesis (Huang & Chen, 2018). Herding suggests that price changes can occasionally be caused by the dynamics of crowd behavior rather than just information.

Because herd behavior can generate price momentum that is unrelated to fundamentals, it poses a serious threat to market efficiency. Important information may not be included into prices when investors follow the herd and disregard their personal information; if everyone is buying despite warning signs, the price may be too high; if everyone is selling despite strong fundamentals, the price may be too low. Herding can lead to significant deviation in the short term, but contrarians or investors who focus on fundamentals may eventually correct these mispricings. For example, empirical research has found herding among retail investors around initial public offerings (IPOs) and popular tech stocks, as well as among mutual fund managers, who occasionally crowd into popular stocks. Although it occurs to some extent in all markets, Spyrou (2013) and other researchers who examine herd behavior find that it is more noticeable in emerging markets and during times of extreme market conditions. Investors who wish to make autonomous, logical decisions must understand the psychological processes behind herding, especially as they relate to media and technology in the contemporary era. As demonstrated by meme stocks and some cryptocurrencies, social media platforms have the ability to quickly start or intensify herding in the modern world. Investors who are conscious of this may take action to "tune out the noise," making choices based on their own research or long-term goals rather than trends. Investors can try to avoid getting caught up in trends that are more motivated by group psychology than by core values by acknowledging the impact of social factors on their decision-making. Some people might even use contrary tactics, looking for opportunities when the herd overshoots (e.g., value investing in stocks that aren't popular or making money when an asset's popularity soars).

In conclusion, institutional herding is frequently observed when funds closely follow benchmarks or mimic each other's allocation shifts, demonstrating that herding is still a common bias in both retail and institutional settings. According to behavioral finance research, herding still has a big impact on investment choices in modern markets, as evidenced by the findings of Bhutto et al. (2025). The potential for herding may even rise with the integration of AI tools (such as sentiment trackers that display "what others are doing/thinking") unless investors carefully distinguish signal from noise. Therefore, maintaining disciplined investment strategies requires an awareness of herding and the ability to recognize when one may be following the crowd.

Key Biases Explored: Status Quo Bias

A psychological tendency known as "status quo bias" causes people to choose to keep things as they are or sticking with past choices over making changes, even when doing so could result in better outcomes. When it comes to investing, this bias shows up as stickiness or inertia in portfolio selections, as investors tend to stick with their default options or current holdings. In their 1988 paper, Samuelson and Zeckhauser formally introduced and documented status quo bias, demonstrating through decision experiments that when presented with options, people strongly prefer "doing nothing" or maintaining the status quo. They showed that, even when objectively outweighed by other options, people were much more likely to select the option that was designated as the status quo in these situations (such as an inherited portfolio). Numerous mechanisms can account for this bias, including cognitive (such as loss aversion and anchoring on the present state), psychological (such as regret avoidance, or a desire for consistency with past decisions), and rational (such as considering switching costs or uncertainty about new options). A disproportionate preference for the status quo is a result of all of these factors.

There is strong evidence that investment decisions are influenced by status quo bias. Samuelson and Zeckhauser (1988) discovered through a series of experiments that even in cases where switching was obviously beneficial, participants would frequently choose to remain in a default investment (for example, a moderate-risk portfolio they "inherited" in the experiment) rather than move to a new portfolio with higher expected returns. In practical terms, this is comparable to investors avoiding opportunities to enhance the performance of their portfolio by simply holding their money in an obsolete mix of assets or a low-yield savings account because that is what they have always done. This bias is caused by several factors. The current situation may seem safer if transition costs are real, such as taxes and fees, or perceived, such as the time and effort required to look into alternative options. "Better the devil you know" and uncertainty about the future also encourage people to hold onto their current investments. Cognitive misperceptions are involved: anchoring uses the current portfolio as a benchmark against which changes are assessed, frequently necessitating a significant perceived gain to support any action. Even when the likelihood of switching is small, loss aversion makes the possible losses seem more significant than the possible gains. Investors may psychologically feel obligated to their previous decisions (the sunk cost fallacy, "I've held this stock for so long, I can't sell it now") or they may wish to avoid the regret of switching strategies only to watch the old choice perform well (regret aversion). The persistence of status quo bias is influenced by each of these elements.

Think about an investor who received a blue-chip stock portfolio from a family member. The investor maintains the initial portfolio basically unchanged for years, even in the face of shifting market conditions and the appearance of new investment opportunities that may offer higher risk-adjusted returns. Status quo bias is demonstrated by this behavior: the inherited portfolio is used as the benchmark, and the psychological comfort of keeping it exceeds the possible advantages of reallocating. "This portfolio has done okay so far, why interfere with it?" or "This change could do more harm than good" are two ways an investor might justify inaction. Employees sticking with retirement plans' default options, such as choosing the same fund or default contribution rate, is another frequent occurrence. Many employees stick with whatever the default enrollment setting is, even when there are better options available, like a more diversified fund or a higher contribution that would be matched by the employer. Long-term results can be greatly impacted by this inertia, frequently in a negative way.

Status quo bias has implications for larger market dynamics in addition to individual portfolios. Markets may react to new information more slowly than would be predicted under full rationality if a sizable percentage of investors display this bias. For instance, a stock's price may stay high for longer than its fundamentals justify if a large number of investors are reluctant to sell a stagnating stock because they merely do not want to alter their holdings (a type of market inefficiency). Furthermore, status quo bias can have intricate interactions with other biases. Combining status quo bias and loss aversion, an investor may be especially reluctant to sell losing investments (they maintain the status quo of holding the loser, in part to avoid realizing a loss). At the same time, they may become overconfident and overestimate the potential of their current holdings, which would further solidify the status quo (thinking, "I chose these stocks for good reasons, I'll trust my original judgment"). Another interaction is with automation bias in the contemporary era: as default options and robo-advisors proliferate, some investors may blindly follow the algorithm's recommendation (a new form of status quo adherence). As evidence that the bias continues into the AI-assisted environment, Shukla and Shukla (2023) discover that even after Indian retail investors begin using digital platforms, many of them will continue to use default fund allocations or refrain from making changes to their robo-advised portfolios. Additionally, that study identified a phenomenon known as "automation bias," in which investors over-relied on automated recommendations, thereby approving the AI's initial recommendations without question (Shukla & Shukla, 2023). This brings to light a new problem: although AI tools can mitigate some biases, if investors become overly passive, they may unintentionally produce a new kind of status quo bias.

A major obstacle to making the best possible investment decisions is status quo bias, which keeps investors from adjusting their portfolios in response to shifting market conditions or individual situations. An initially well-chosen portfolio may eventually become less than ideal (for example, too heavily weighted in a once-favored sector that is now underperforming, or with an inappropriate risk level as the investor ages). Opportunity costs, lost profits from better investments, and suboptimal risk exposure, too much or too little risk in relation to the investor's objectives, can all be consequences of the tendency to "leave things as they are." A strong theoretical framework for understanding this bias is offered by the original research conducted by Samuelson and Zeckhauser (1988), which emphasizes its complex nature and widespread influence across decision domains. The existence of status quo bias in real investor behavior has been validated by later empirical research. For instance, research on 401(k) retirement plans in the United States revealed that inertia is a powerful force: unless pushed to do otherwise, many employees maintain their default asset allocations and contribution rates (Madrian & Shea, 2001). This resulted in the creation of target-date funds and automatic escalation to combat inertia. In a similar way, researchers have found that a significant portion of investors in brokerage accounts hardly ever rebalance or modify their portfolios, despite the fact that fundamental portfolio theory dictates that they should (Agnew et al., 2003).

The first step in combating the status quo is acknowledging its strong pull. Investors can create plans for routine portfolio reviews with specified criteria for change as a way to combat this bias. To force a mechanical, not emotional, change from the status quo, an investor might, for example, establish a rule requiring their portfolio to be rebalanced to target weights annually. Seeking outside opinions is another strategy. A financial advisor or an informed friend can question an individual's attachment to current holdings ("Why are you still holding this stock?") A focus on default options that benefit investors' long-term interests has emerged in corporate finance as a result of awareness of the status quo bias (e.g., defaulting employees into adequately aggressive retirement portfolios when young, because many will stick with the default). The main idea is that because status quo bias is deeply rooted in our emotional comfort zones and cognitive processes, it often requires external or structural interventions to overcome. Some robo-advisors in the AI era deal with this by automatically rebalancing or suggesting portfolio adjustments on a regular basis, thereby serving as a counter-bias mechanism to shake investors out of their complacency. But as mentioned, a balance must be struck to prevent automation from simply becoming a new norm that investors blindly accept (Dietvorst, Simmons, & Massey, 2015).

In conclusion, investors are still frequently influenced by status quo bias, which may make it more difficult to respond quickly to fresh information or better opportunities. Investors and advisors can employ strategies to lessen its effects by being aware of its causes, justifications, cognitive anchoring, and emotional comfort. Making more responsive and dynamic investment choices in the constantly shifting financial markets requires this.

Impact of These Biases on Investment Outcomes

Overconfidence, herd behavior, and status quo bias are behavioral biases that have a big influence on investment results. They frequently result in less than ideal financial outcomes and inefficiencies in the market. Research continuously demonstrates a pattern of widespread influence on decision-making processes and evident repercussions for market dynamics, portfolio performance, and even general economic welfare across all of these biases. Market participants and regulators trying to negotiate the complex dynamics of behaviorally influenced markets, as well as investors hoping to enhance their financial results, must understand these effects.

These biases can have quantifiable detrimental effects on investment returns, as empirical evidence repeatedly shows. Overconfidence, for instance, usually results in excessive trading, which raises transaction costs and frequently leads to poorly timed entry and exit decisions. Even after controlling for market conditions, Bouteska et al. (2023) demonstrated that overconfident investors who traded more frequently in 2016–2021 had lower net returns than those who traded less frequently in the U.S. market. They discovered that overconfident investors continued to trade actively despite declining performance, effectively trading against their own best interests, even during times of extreme uncertainty, like the initial COVID-19 outbreak in 2020. The fact that these investors may have thought they could "trade their way" out of losses or that the next opportunity would undoubtedly be a winner, rather than cutting back on trading when results were poor (which would be a reasonable response), highlights how obstinate the bias can be. In a similar vein, herd behavior frequently causes investors to follow market trends and buy high or sell low, which is contrary to the well-known the rule "buy low, sell high." Herding is a common phenomenon where investors gather into popular assets near their peak and then exit in large numbers during downturns. Bhutto et al. (2025) found that herding significantly influenced investment decisions. As a result of this behavior, many investors effectively buy at market peaks and sell at bottoms, which reduces returns. Investors' unwillingness to alter their holdings may prevent necessary portfolio adjustments, resulting in opportunity costs and inefficient asset allocations, as demonstrated by Samuelson and Zeckhauser's (1988) research on status quo bias. Due to status quo bias, an investor who hangs onto a declining stock may lose out on the opportunity to use that money for a more promising asset, which would have reduced their potential return. Such lost opportunities (or a failure to adjust to changes in the market system) add up to a significant performance gap over time.

These effects are demonstrated by specific real-world examples. Many individual investors displayed typical herd behavior and overconfidence during the 2017 cryptocurrency boom. Instead of rebalancing or taking profits, they poured more money into cryptocurrencies as prices rose, driven by initial profits and hype. When the cryptocurrency market crashed in 2018, Bitcoin lost a significant amount of its value due to excessive trading and trend-chasing. The repercussions of buying high were felt by those who followed the crowd into cryptocurrency at its height, possibly thinking that "it's different this time" or that they had better insight. Even though avoiding the crash was fortunate in hindsight, investors with status quo bias who kept only traditional portfolios and completely disregarded cryptocurrency may have missed out on the early diversification benefits and remarkable gains during the run-up. The early 2000s dot-com bust serves as another illustration. Herd behavior and overconfidence drove tech stocks to exaggerated valuations, and when reality set in, markets crashed. Before some of those companies recovered (and many never did), investors who stuck to their once high-flying tech stocks (status quo bias) experienced years of poor returns. Whether it was missed opportunities due to inertia or loss of wealth from bubble participation, a different bias (or combination of biases) resulted in a specific type of suboptimal outcome in each of these scenarios. These situations also demonstrate how biases can lead to various dangers based on the timing and market context.

The detrimental effects of biases can be aggravated by their interactions. Biases rarely function independently; for example, an investor may be overconfident and swayed by the herd. When this happens, an investor's initial decision to place a significant bet on a well-liked asset may be motivated by overconfidence. Herd behavior may then confirm the investor's belief as they observe others joining in, intensifying their exposure (and possible loss). The investor may be trapped in a losing position by all three biases if the investment starts to go wrong because status quo bias may then prevent them from reducing their losses. In their analysis of these relationships in relation to investment choices and dividend policy, Bhutto et al. (2025) discovered that behavioral factors can produce feedback loops that intensify market inefficiencies. A bubble can be inflated, for instance, by herd behavior and general overconfidence (e.g., housing in 2005-2007). An overshoot on the downside (prices falling too far) may result from the panic (herd selling) and possibly regret aversion that follows the bubble burst. Persistent market anomalies like momentum, an initial underreaction brought on by status quo bias, followed by an overreaction driven by the herd, and reversal patterns are explained by these intricate dynamics. These phenomena are difficult to explain by traditional finance models, which presume independent rational actors; in contrast, a behavioral lens that takes bias interactions into account tells a more coherent story.

These biases have an effect on economic stability and market efficiency more broadly than just individual portfolios. Price signals may become distorted, at least temporarily, when a sizable fraction of market participants display biases. Long-term price deviations from fundamental values can cause the economy's capital to be misallocated (for example, too much money going into speculative endeavors during a bubble, or productive companies starving of capital during a pessimistic phase). Real economic costs may result from such misallocations, such as underinvestment in particular industries or the formation of asset bubbles that burst and cause recessions (as was arguably the case with the housing bubble and subsequent financial crisis in 2008). Research on all three biases indicates that their effects are not just theoretical but also have real-world economic repercussions that can be seen in data. Even complex markets with numerous institutional players are prone to behavioral influences, according to Bouteska et al. (2023), who discovered evidence of overconfidence in U.S. markets up until 2021. Likewise, research on the persistence of mutual fund performance frequently attributes outperformance followed by reversion to manager overconfidence or herding into crowded trades. The fact that biases continue to exist in a variety of market environments highlights how fundamentally they influence results. It also implies that even with more sophisticated digital tools available to investors, human-led market inefficiencies are unlikely to disappear anytime soon. Ironically, even quantitative trading models can display biases if they are created or adjusted by people who share particular opinions. For example, in August 2007, a number of quantitative models failed at the same time, in part due to the fact that they were based on similar data and assumptions, which is a type of herd behavior in model building.

There is hope that some of these biases can be reduced in the era of artificial intelligence. For instance, algorithmic trading can provide liquidity when people withdraw out of fear, and robo-advisors may promote discipline against overtrading. AI is not a perfect solution, though, as it can reflect the biases of its developers or introduce new complexities and biases (such as automation bias). It is clear that improving investment results requires an understanding of and ability to control behavioral biases. Nowadays, a lot of practitioners use behavioral finance techniques: advisors use surveys to assess their clients' biases, fintech apps encourage users to adopt healthy habits (such as long-term investing or proper diversification), and educational programs inform investors about these dangers. From a regulatory standpoint, knowing these biases can help shape policies. For instance, identifying herd behavior may result in more strict disclosure requirements or circuit breakers to calm crazed markets. In conclusion, status quo biases, herd behavior, and overconfidence have a significant impact on both individual and societal financial well-being. We can learn why markets occasionally act "irrationally" and how to potentially address or profit from these behaviors by researching their effects. Theoretical frameworks that are helpful in explaining why people constantly display these biases when making decisions in the face of uncertainty are covered in the following sections.

3.2 Risk Tolerance in Investment Decision-Making

Definition and Classical Understanding of Risk Tolerance

Risk tolerance refers to an investor's ability and willingness to endure declines in the value of investments while pursuing financial goals. Traditionally, finance theory has treated risk tolerance as a relatively stable, intrinsic attribute that influences portfolio selection and asset allocation (Grable, 2000). According to traditional models like Modern Portfolio Theory (Markowitz, 1952), investors maximize expected return for a given level of risk by using risk tolerance as a key input to construct the efficient frontier. While investors with low risk tolerance would favor safer assets (like bonds), those with high risk tolerance are anticipated to allocate more heavily into volatile, high-return assets (like stocks).

However, risk tolerance was viewed by early financial theories as being constant over time and mainly based on rational utility maximization. According to this perspective, unless there are important life changes like retirement or significant financial shocks, an investor's risk tolerance should stay constant given consistent preferences and reasonable expectations (Grable & Lytton, 1999). As a result, a large portion of conventional financial advising procedures focused on evaluating a person's risk profile once, using questionnaires or interviews, with little regard for how risk preferences might change over time.

Behavioral Finance Insights: Risk Tolerance as Dynamic and Context-Dependent

By showing that people's willingness to accept risk is dynamic and heavily context-dependent, behavioral finance questioned the notion of stable risk tolerance. Depending on their reference points, people behave risk-aversely when they face gains and risk-seekingly when they face losses, as demonstrated by Kahneman and Tversky's (1979) Prospect Theory. This "reflection effect" suggests that risk tolerance is a variable that can change depending on emotional states, recent experiences, and framing.

According to research, perceived risk tolerance is strongly influenced by market conditions. For instance, Guiso, Sapienza, and Zingales (2018) discovered that investors' appetite for risk drastically decreased following a financial crisis, indicating increased loss sensitivity. In the same direction, Hoffmann, Post, and Pennings (2015) noted that investors' risk tolerance is procyclical, tending to rise in bull markets as confidence rises and fall in bear markets as fear takes over.

Furthermore, psychological biases like herd behavior, overconfidence, and loss aversion affect risk tolerance (Kahneman & Tversky, 1979; Barber & Odean, 2001). People with loss aversion are more risk averse than conventional models would suggest because they overestimate possible losses in comparison to comparable gains. Investors who are overconfident may undervalue risks, which will increase their perceived risk tolerance. However, as investors follow the herd, herding may affect risk perceptions, leading to an underestimation of downside risks during times of general optimism (Bhutto et al., 2025).

These insights imply that understanding and managing risk tolerance requires more than a one-time static assessment; it requires ongoing monitoring and adaptation, particularly during periods of market volatility or personal financial stress.

Determinants of Individual Risk Tolerance

Numerous studies have found important factors that impact a person's risk tolerance, indicating that it is a complex construct influenced by both situational and stable factors.

-**Demographics**: It has been discovered that risk tolerance is correlated with age, income, education, and gender. Because they have longer investment horizons, younger people tend to be more risk tolerant, whereas higher income and educational attainment are typically linked to a greater capacity for taking risks (Grable, 2000).

-**Personality Traits**: Variations in risk tolerance have been associated with psychological traits like conscientiousness, emotional stability, and openness to new experiences (Lather, Jain, & Anand, 2020). More precisely, an increased readiness to accept investment risk is predicted by higher extraversion and lower neuroticism.

-**Experience and Financial Literacy**: Having more financial knowledge and prior investment experience can increase one's risk tolerance, but if it isn't balanced by an understanding of the unpredictability of the market, it can also result in overconfidence (Kumar & Prince, 2023).

-**Cultural and Social Factors**: How people view and handle investment risk can also be influenced by cultural views on avoiding uncertainty, social influences, and media exposure (Hossain & Siddiqua, 2022).

Understanding these factors is crucial for creating personal investment plans and comprehending how risk tolerance can change over time.

Measurement of Risk Tolerance in Investment Practice

In reality, self-report questionnaires that measure an investor's comfort level with speculative losses, volatility, and fluctuating return scenarios are frequently used to evaluate risk tolerance. People are frequently categorized into various risk profiles using instruments like the Grable and Lytton Risk Tolerance Scale (1999). However, these approaches are susceptible to biases such as framing effects and social desirability bias.

Other methods have surfaced, such as psychometric tests that aim to capture more profound cognitive and affective reactions to risk and behavioral measures (such as watching real investment decisions made in an experimental setting) (Faff, Hallahan, & McKenzie, 2009). Technological developments in recent years have made it possible to conduct dynamic risk profiling, in which an investor's actions and reactions to market developments are continuously observed in order to gradually improve their risk assessment.

Robo-Advisors and Risk Profiling

In order to classify clients into risk groups consistent with contemporary portfolio theory, robo-advisors usually begin the onboarding process with thorough risk profiling questionnaires (D'Acunto, Prabhala, & Rossi, 2019). Robo-advisors, in contrast to traditional advisors, frequently include ongoing feedback loops, adapting portfolio recommendations in response to shifts in client behavior and market conditions. A robo-advisor might, for example, recalculate an investor's risk profile downward or encourage them to reevaluate their risk tolerance and objectives if they engage in panic selling during a downturn.

Furthermore, emotional biases that influence risk perception can be mitigated by robo-advisors. According to Back, Morana, and Spann (2023), robo-advisory platforms can help investors maintain strategies that are in line with their true risk tolerance rather than one that is distorted by the circumstances by mitigating behavioral biases like the disposition effect. Although anthropomorphic interfaces and other social design components of robo-advisors can occasionally unintentionally reintroduce emotional biases, careful design is necessary to maximize their impact on risk management (Hildebrand & Bergner, 2021).

Dynamic Risk Adjustment and AI Algorithms

The ability of sophisticated AI algorithms to adjust portfolio risk in response to sentiment analysis, real-time data, and macroeconomic indicators is growing. For instance, sentiment analysis tools can evaluate the general mood of the market and modify portfolio allocations to prevent exposure to increased volatility (Fatouros et al., 2023). Compared to static risk profiling, such capabilities allow for more sophisticated risk management.

However, there are worries that dynamic changes might unintentionally make procyclical behavior worse. AI systems may worsen downturns by reducing risk exposure across multiple portfolios at once in response to negative sentiment, strengthening rather than reducing collective risk aversion (Arumugam, 2023). Therefore, even though AI tools have the potential to improve individualized risk management, systemic risks must be avoided by carefully calibrating them.

Potential Amplification or Mitigation of Biases

AI tools have the potential to both reduce and amplify biases that influence risk tolerance. On the one hand, automation makes risk management more consistent by protecting investors from instinctive, System 1-driven decisions (Kahneman, 2011). However, automation bias can affect investors' risk perception and cause them to embrace excessive conservatism or inappropriate risk levels if they place an undue amount of trust in AI outputs without critically analyzing them (Dietvorst, Simmons, & Massey, 2015).

Therefore, tool design, transparency, and investor education have a significant impact on how AI ultimately affects investor risk tolerance. Investors can use System 2 thinking to better understand and manage their risk preferences over time by using transparent AI systems that provide an explanation of the reasoning behind portfolio adjustments.

Evolution of Risk Tolerance in an AI Environment

There are still a lot of unanswered questions about how AI tools will affect risk tolerance in the long run, even though their use in investment management is expanding. It's unclear if using AI advice eventually results in more consistent and sensible risk preferences or if it encourages dependence and diminishes financial independence (Lopez, 2022). In a similar vein, little is known about the differential effects across investor demographics, such as whether younger, tech-savvy investors adjust their risk tolerance in a different way than older generations.

Future studies could examine the effects of extended use of AI tools on investors' capacity to self-regulate without the aid of technology, internalize risk concepts, and remain resilient during market downturns. Designing AI systems that really enable investors rather than just automating their biases requires an understanding of these dynamics.

To sum up, risk tolerance is still a crucial, yet dynamic, aspect of investing decision-making. Behavioral finance demonstrated its dynamic and situational nature, whereas classical finance stressed its stability. Although AI tools present new ways to better evaluate and control risk tolerance, they also bring with them new challenges that need to be carefully handled to support the best possible outcomes for investors.

3.3 Theoretical Frameworks

Dual Process Theory (System 1 & System 2): Description and relevance to investor decision-making

A strong framework for recognizing the mental processes that guide investor decision-making is offered by dual process theory. This theory, which was developed in cognitive psychology and made popular by Daniel Kahneman and others, makes a distinction between two different ways of thinking, commonly referred to as System 1 and System 2, which have a major influence on how investors interpret data and make decisions. System 1 uses pattern recognition instead of conscious analysis to function quickly and naturally. It relies on emotional reactions and heuristics, or mental shortcuts, and doesn't require much conscious effort. System 1 is defined by Renevier (2024) as "your gut reaction, the instinctive decisions you make without even realizing it." When investors respond instantly to market news or price changes, System 1 is obvious in the context of investments. System 1-triggered behaviors include, for instance, panicking and selling when a stock falls or experiencing a sudden urge to purchase a stock after witnessing its price abruptly spike (possibly due to FOMO). System 1 is effective and helpful for routine decisions that don't call for in-depth analysis; it's what allows someone to drive a familiar route on "autopilot" or duck when a ball is thrown at them. But when it comes to investing, System 1 can cause rash, emotionally motivated decisions that frequently produce less-than-ideal results. Because it is automatic, it is prone to cognitive biases, heuristics can go wrong (for example, chasing trends when using a stock's recent performance as a method for its future prospects), and emotional responses (such as fear and greed) may interfere with sound judgment.

Let's take an example where an investor is informed that a stock in their portfolio has experienced a 15% decline in a single day. An instantaneous panic attack and the desire to "stop the bleeding" by selling the stock could be System 1 reactions. This reaction occurs prior to any analytical evaluation of the reasons behind the stock's decline; it may be an overreaction by the market, a brief earnings miss, or a general market decline. However, System 1, motivated by the instinctive unease of witnessing a loss, advises the investor to take action immediately and consider it later. Such an emotionally motivated sell could unnecessarily lock in a loss, particularly if the stock's fundamentals hold up and it later recovers. In a similar vein, System 1 may encourage an investor to participate in a popular IPO simply because social media users are enthusiastic about it and the stock is rising, a herd behavior that occurs without stopping to consider valuation. These instances show how, despite its speed, System 1 can mislead investors by giving more weight to gut instincts and straightforward correlations than to rigorous analysis.

System 2, on the other hand, stands for the brain's methodical, slow, and analytical thought process. It calls for deliberate effort, focus, and the application of reason and logic. System 2 is described by Renevier (2024) as "the voice in your head that says, 'Hold on, let's think this through.'" When an investor uses System 2, they look closely at financial data, such as analyzing a company's earnings report, assessing economic indicators, comparing the price of an asset to its intrinsic value model, etc. An investor may use System 2 to balance the benefits and drawbacks of a potential investment, take into account other possibilities, and match choices to risk tolerance and long-term objectives. Generally speaking, this methodical approach is linked to more sensible and informed investment decisions. When a System 2-driven investor receives a 10% drop notification, for example, they might pause and look into why this occurred. Is there a fundamental problem or is the market overreacting? If their research indicates that the stock is now cheap, they may choose to hold onto it or even purchase more. On the other hand, System 2 may decide to sell if analysis identifies a significant issue (such as a fraud allegation), but this choice would be made rationally rather than in a panic. By saying, "I know it feels bad that this stock is down, but my analysis shows the business is still strong, so I shouldn't sell," System 2 can override an emotional impulse and serve as a check on System 1's impulses. Like a muscle that gets exhausted, System 2 is slower and requires more work. Because using System 2 requires focus and occasionally willpower, people frequently fall back on System 1, especially when under stress or cognitive load.

The Dual Process Theory has significant implications for understanding investor behavior and identifying strategies to optimize investment results. System 1 frequently controls decision-making, especially in situations that are commonly relevant to investing: uncertainty, time constraints, emotional engagement, and an abundance of information, as demonstrated by Kahneman's work (Kahneman, 2011) and others. According to Renevier (2024), System 1 typically takes the lead when decisions need to be made fast or when an individual is navigating complex, overwhelming information, situations that are typical in volatile markets or during breaking news. Even expert, well-informed investors can make irrational decisions, which is explained by System 1's dominance in many financial situations. It is often the result of an emotional or methodic reaction from System 1 short-circuiting their corresponding System 2, rather than a lack of knowledge. Confirmation bias, for instance, can be defined as System 1's tendency to observe and retain information that supports preexisting opinions (it feels good to have one's opinions validated), while System 2 requires effort to find or fairly consider contradicting evidence. Unless they actively use System 2 to combat that bias, an investor who has a strong belief in a particular stock may have their System 1 automatically downplay bad news about it.

Investors need to understand how these two systems interact in order to control their own decision-making. Knowing that an instinct may be merely an emotional whim or heuristic allows one to postpone taking action until a more thorough analysis is completed, thereby allowing System 2 to catch up. Practical strategies to use System 2 more frequently include keeping an investment journal to document the reasoning behind decisions or an investment checklist to systematically assess every trade. These tools transform what could have been an impulsive action into a more intentional process by forcing a pause for introspection.

Establishing rules, such as "I will not buy a stock the same day I hear about it; I will research for a week first," is another tactic. Disciplined investors frequently use these rules to prevent System 1 impulses. Another System 2 enforcing strategy is to play "devil's advocate" with your own ideas (or have an investment partner who does so). This involves purposefully challenging your initial intuition by posing the question, "What could go wrong? What have I been missing?" This encourages analysis as opposed to just intuition.

Dual Process Theory also sheds light on market behavior from a wider angle. Collectively, biases such as herd behavior, momentum, and overshooting occur when a market event sets off mass System 1 reactions (such as a panic or a mania). The market as a whole may deviate from the fundamentals until System 2 thinking (possibly by value investors or arbitrageurs) corrects it if the majority of market participants are responding impulsively (System 1) rather than thoughtfully. Markets dominated by institutional investors, who are not immune to bias but frequently have procedures to enforce more analysis, appear to be somewhat more efficient than those with a higher percentage of retail investors, who may be more likely to engage in System 1 trading in the short term. Even professionals, however, are susceptible to System 1, for example, when under stress or when they depend on their experience-based intuition, which may be misleading in situations that are unfamiliar.

In conclusion, Dual Process Theory recommends that people should make an effort to use System 2 when it comes to making better investment decisions, particularly when it comes to significant choices like asset allocation, security selection, and the timing of significant trades. Although System 1 is not "bad," it does offer intuition and can be supported by experience (experts frequently have good instincts in familiar domains). However, because of the influence of emotions and biases, System 1 has many risks when it comes to investing. Investors who understand the two systems can learn to spot emotional or System 1 reactions and then step back to let reason take over. This is more crucial than ever in the era of rapid information and AI trading. Ironically, although AI may automate System 2-type analysis for us (such as parsing data and crunching numbers), it may also make our human System 1 just as vulnerable to greed and fear as it was in the past. As a result, behavioral finance experts continue to strongly advise both individual and institutional investors to develop System 2 habits.

Dual-Process Theory and the Cognitive Regulation of Risk Tolerance

The cognitive foundations of fluctuating risk tolerance are further explained by Dual-Process Theory (Kahneman, 2011). Overhyped buying during rallies or panic selling during downturns are examples of how System 1, the quick, intuitive, and emotional way of thinking, frequently controls immediate responses to market events. The slower and more analytical System 2 mode, on the other hand, is able to more carefully evaluate risk and adjust investment behavior in order to achieve long-term objectives.

Thus, the relationship between System 1 and System 2 influences risk tolerance. System 1 takes over under stress or feelings of excitement, which causes abrupt and frequently illogical shifts in risk appetite. By encouraging thoughtful decision-making, System 2 may balance risk preferences when it functions well. The oversight capacity of System 2 over fluctuating risk tolerance is demonstrated, for example, by investors who, following a steep decline, take the time to assess market fundamentals instead of selling on impulse.

Prospect Theory: Core principles and implications for risk perception and decision-making

Our understanding of decision-making in relation to risk has been completely transformed by the innovative framework known as Prospect Theory, which was created by Daniel Kahneman and Amos Tversky in 1979. It emerged as a critique of the expected utility theory, which had long been the dominant model describing rational decision-making under uncertainty. Kahneman and Tversky developed a different model that more accurately explains observed choices after conducting extensive experiments and discovering a number of common behaviors that defied the expectations of expected utility theory.

Prospect theory's fundamental ideas focus on how people assess possible gains and losses in relation to a reference point, typically the status quo or an expectation, rather than in pure terms of wealth. One important feature is the "certainty effect," which is the tendency for people to place more weight on outcomes that are certain than those that are only likely. According to research by Kahneman and Tversky (1979), people frequently favor a certain gain over a larger expected gain with a degree of risk, and they also favor a risky gamble over a certain loss, even if the gamble has a higher expected loss. If we consider a choice that is presented in terms of profits: (A) a guaranteed $400 increase or (B) a 65% chance of gaining $700 (and a 35% chance of gaining nothing). Even though the gamble's expected payoff is $455 (0.65 × $700), most people still prefer the certainty of $400, demonstrating risk aversion when results are favorable. When the same numbers are placed in the loss domain (A) an assured $400 loss versus (B) a 65% chance of losing $700 (and a 35% chance of losing nothing), many people abruptly shift to the gamble, accepting an expected loss of $455 instead of the certain $400, demonstrating a preference for risk over losses. The rationality principle of invariance is violated by this reversal, which also highlights prospect theory's asymmetric value function, concave for gains, convex for losses, and the crucial role of framing. For example, saying you "keep $300 of a $700 windfall" feels very different from saying you "lose $400 of that $700," even though the net result is the same.

The "isolation effect," where people tend to overlook elements shared by all prospects and concentrate only on differences, was also discovered by Kahneman and Tversky's experiments. When essentially the same option is offered in various formats, this may result in inconsistent preferences. For example, if the reference points or descriptions of two equivalent formulations of a gamble are different, people may make different choices. The rational assumptions that govern conventional economic models were directly called into question by these findings, which demonstrated that actual human decisions are impacted by more than just ultimate states of wealth. These factors include the certainty vs. risk dichotomy and the framing of options.

Prospect Theory's value function, which takes the place of classical theory's utility function, is a key component. The value function has three essential features and is defined over gains and losses in comparison to a reference point rather than over total wealth: (1) It typically has a S shape, with gains being concave and losses being convex. This illustrates diminishing sensitivity: the subjective value difference between $100 and $200 appears to be greater than that between $1,100 and $1,200 (diminishing sensitivity for gains), and the same is true for losses. (2) According to many estimates, it is asymmetric, steeper for losses than for gains, and represents loss aversion. Losses hurt roughly two to 2.5 times as much as equivalent gains feel good. (3) It crosses the reference point (0 change) in such a way that the large jump in value when going from a gain to a loss is reflected by a kink at 0. Several observed behaviors can be explained by this value function form: People strongly avoid decisions that involve possible losses (loss aversion), and they are risk-averse in gains (concave part) and risk-seeking in losses (convex part). People may turn down a fair gamble (50/50 win $1100 vs. lose $1000, for example) because they are more afraid of losing $1000 than they are of winning $1100. This is explained by loss aversion. It also explains phenomena like the endowment effect, which states that people value an item they own more than the same item they do not because giving it up is seen as a loss (which is felt more keenly) rather than as forgoing a gain. Experiments have shown the endowment effect, which reflects that once something becomes a part of one's reference point (owned), losing it is painful (Samuelson & Zeckhauser, 1988 discuss similar commitment effects). For example, people who are given a mug will demand more money to sell it than others are willing to pay to buy it. This value function also relates to the disposition effect in investing, which occurs when winners are sold too soon and losers are held for too long. While realizing losses is extremely painful (so people put it off), realizing gains feels good but has diminishing returns. As a result, investors typically avoid crystallizing losses (risk-seeking in losses by holding on, hoping to get back to even) and lock in small gains (risk-averse in gains). Standard finance was unable to readily explain this otherwise perplexing behavior, but Prospect Theory offers an explanation.

Prospect theory has major implications for how investors perceive risk and make decisions. The idea of decision weights, which take the place of probabilities in the theory, is one significant component. People tend to underweight moderate to high probabilities and overweight small probabilities; they do not treat probabilities in a linear fashion. Because they overestimate the likelihood of winning a jackpot (which makes gambling appealing) and the likelihood of a disaster (which makes insurance appealing), this can help explain why some people choose to gamble and purchase insurance. This tendency may devalue fairly safe bets and make lottery-like stocks (very small chance of huge payoff) overly attractive (investors overweight the tiny chance of a massive win). The enduring demand for out-of-the-money options or speculative penny stocks with low expected returns can be explained by human nature's tendency to seek high skewness, or a slim chance of a large win. It may also be a factor in asset pricing challenges, such as why initial public offerings (IPOs) or some flashy stocks may be overpriced, as investors overestimate the likelihood that the business will become the next Apple or Microsoft.

The focus placed by Prospect Theory on framing and reference points highlights how investor behavior and satisfaction can be significantly impacted by how options are presented or how results are perceived in comparison to expectations. For example, even though they ended up with the same result, an investor who expected a 10% return but received 5% may feel disappointed (a loss relative to expectation), while another who expected 0% and received 5% feels happy (a gain relative to expectation). This may have an impact on their future risk-taking behavior (a dissatisfied investor may increase their risk in an attempt to "catch up," demonstrating risk-seeking in the context of losses). In a similar way, fund managers are frequently assessed in relation to benchmarks; even if the fund had a positive return, a loss relative to the benchmark is psychologically a "loss," which could lead to herding or short-term behavior to avoid that loss.

According to Prospect Theory, investors may have varying risk appetites for each of the buckets they mentally split their investments into (mental accounting) in order to manage their portfolios practically. For instance, they might handle a "for fun" trading account (willing to gamble) differently than a retirement account (don't want to see losses here, very loss averse). If not handled appropriately, this can result in a less-than-ideal overall allocation; however, many people manage risk psychologically by having both a speculative and a safe core portfolio.

Financial advisors can gain a deeper understanding of client behavior through applying the insights of Prospect Theory. For instance, advisors frequently highlight strategies that reduce the likelihood of losses or at the very least frame outcomes in ways that align with client reference points because they know that their clients dislike losses far more than they enjoy comparable gains (e.g., concentrating on long-term growth to frame short-term declines as mere negligeable in comparison to a longer perspective). Additionally, it implies that financial education could help in adjusting points of reference (e.g., establishing reasonable expectations to prevent framing typical market volatility as intolerable losses).

In conclusion, Prospect Theory explains a number of investing behaviors, such as why people may invest in safe assets and speculative bets at the same time, why they hold losers (disposition effect), why volatility reduces investor utility more than symmetric gains help (explaining a high equity risk premium, investors require large compensation to take on stocks because the volatile losses are very painful), and why structured products that offer principal protection (no loss, but capped upside) find buyers because loss-averse investors highly value eliminating the possibility of loss (a reference point guarantee), even at the expense of some upside. The main argument of the theory is that people's decisions are significantly influenced by how they view results, whether they are gains or losses, and that losses seem more significant than gains. Prospect Theory is a useful way of approaching any analysis of risk tolerance or investment decision-making biases (like this thesis), as it focuses on the psychological value attributed to outcomes, which improves Dual Process Theory's cognitive perspective.

Prospect Theory and the Context-Dependence of Risk Tolerance

According to Prospect Theory (Kahneman & Tversky, 1979), people assess results in relation to a reference point rather than in absolute terms. This framework demonstrates how investors become risk-seeking when faced with potential losses but risk-averse when faced with potential gains. The "reflection effect" describes how a person's risk tolerance can change based on whether they believe they are in a gain- or loss-oriented domain. A key element of Prospect Theory, loss aversion, intensifies this dynamic by making losses seem more significant than comparable gains. As a result, an investor's risk tolerance is a variable response that is impacted by expectations, recent results, and framing rather than a fixed input.

This explains conditions such as the "disposition effect," in which investors hold losing assets longer than winning ones, in the context of investments. According to Prospect Theory, risk tolerance is a situation-dependent, fluid trait rather than a fixed one, which explains why identical people may behave very differently in bull and bear markets.

Implications for AI Investment Tools

The potential role of AI investment tools in regulating investor behavior is further highlighted by examining risk tolerance through the prisms of Prospect Theory and Dual-Process Theory. As external "System 2" agents, robo-advisors and algorithmic systems can enforce discipline and limit emotional responses that distort risk tolerance. These technologies help in reversing the emotionally motivated and context-dependent changes in risk tolerance that behavioral theories describe by automatically rebalancing portfolios or warning against investing during periods of market euphoria.

Over-reliance on AI, however, carries the risk of limiting investors' own System 2 engagement, promoting automation bias and reducing financial autonomy. As a result, even though AI provides strong tools for stabilizing risk tolerance, its design must promote critical engagement and investor understanding rather than submission.

All things considered, incorporating risk tolerance into Prospect Theory and Dual-Process Theory offers a more comprehensive, behaviorally informed framework for examining investor behavior in the AI era. AI has the potential to significantly impact risk tolerance's stability over time. Risk tolerance is not a static trait; rather, it is a dynamic, situational response influenced by cognitive processes and emotional framing.

3.4 AI Investment Technologies

Robo-Advisors: How they work, benefits, and limitations

Robo-advisors have emerged as significant technological innovations in the investment landscape, fundamentally altering how investors interact with financial markets. These digital financial service agents with artificial intelligence capabilities offer automated investment advice that claims to help people make better investment choices. The fundamental function of robo-advisors is their capacity to evaluate market conditions and investor data in order to produce tailored portfolio recommendations, frequently at a fraction of the price of conventional human advisors (D'Acunto et al., 2019). Robo-advisors can continuously adjust portfolios and adapt asset allocations based on predetermined risk profiles by using algorithms and contemporary portfolio theory (Beketov et al., 2018; Eichler & Schwab, 2024). Even small investors can now access sophisticated financial services that were previously only available to high-net-worth clients thanks to this data-centered approach (Jung et al., 2018).

The ability of robo-advisors to reduce behavioral biases is one way that their influence on investor behavior is especially clear. The availability of a robo-advisor lowers investors' disposition effect, which indicates a higher inclination to realize past gains than past losses, according to research by Back et al. (2023). Investors who had access to robo-advice in a controlled experiment were less hesitant to sell assets at a loss than those who did not. According to this data, robo-advisors can assist investors in overcoming mental obstacles that usually result in less-than-ideal outcomes. This advantage is supported by other research. For instance, D'Acunto et al. (2019) discovered that the use of a robo-advisory portfolio optimizer improved diversification and decreased biases such as rank effects and disposition among Indian brokerage clients. Similarly, a recent review of the literature by Darskuviene & Lisauskiene (2021) finds that although robo-advisors can reduce some biases and generally encourage more disciplined investing, their efficacy varies depending on the situation and the investor. A particular example of how AI tools may enhance financial decision-making and have a positive impact on investor behavior is the mitigation of the disposition effect.

For example, emotional attachment to the original purchase price often blocks rational action when an investor must decide whether to sell a losing stock. By recommending sales based purely on anticipated future performance rather than the purchase price, a robo-advisor, which is emotionally neutral, can help investors avoid the risk of holding onto losing investments for an extended period of time. One real-world example is when a robo-advisor recommends selling a technology stock that has lost value and has bad prospects for the future, even though the investor is reluctant to accept the loss, and reinvesting the money in more promising assets. This behavior is consistent with tax-loss harvesting techniques that certain robo-advisors automatically employ, which not only collect tax advantages but also promote prompt loss realization (Oehler & Horn, 2024). These tools combat investors' innate loss aversion and inertia by offering objective, algorithmic advice, which may result in better outcomes. Investors who used robo-advisors with automated rebalancing and loss-harvesting were, in fact, more likely to cut losses and rebalance into undervalued securities during the COVID-19 market volatility, while many human investors held onto their losing positions out of bias and fear (Shukla & Shukla, 2023).

However, robo-advisors' efficiency varies depending on the implementation. These AI tools' impact on investor behavior is greatly influenced by their design. Programming robo-advisors with social design features (such as naming the advisor after a human and enabling natural language communication) can have a negative impact on investment outcomes by enhancing the disposition effect, according to Back et al. (2023). According to their research, giving the robo-advisor anthropomorphic characteristics decreased the likelihood that investors would ask for its advice, thereby decreasing the debiasing effects of the tool. Making robo-advisors more "human-like" may actually reintroduce some of the psychological obstacles they are designed to help people overcome, according to this surprising discovery. Investors sought advice from a robo-advisor with a persona less frequently, presumably out of embarrassment or fear of being judged, which would not occur with a more impersonal digital interface. This is explained by the way these social design elements impact advice-seeking behavior. Other studies have noted similar trends. Hildebrand and Bergner (2021) demonstrated that conversational robo-advisors, or chatbot-style interfaces, can generate higher affective trust from users than static interfaces. However, this enhanced relationship and confidence may result in miscalculated risk-taking, such as accepting excessively aggressive portfolio recommendations because of a false sense of security. Anthropomorphic features are essentially a double-edged sword: they increase user engagement and trust, but they can also lead to investors making less-than-ideal decisions or using the advice platform less frequently (Hildebrand & Bergner, 2021). These subtleties show that careful design decisions that take into consideration the psychology of human-AI interaction are necessary for robo-advisors to be effective.

A major step toward democratizing the use of financial advising services is represented by robo-advisors. They are useful resources for investors of all income levels due to their capacity to offer reliable, unbiased advice at scale and at a reasonable cost (Back et al., 2023). Robo-advisors can perform complex optimization tasks and round-the-clock portfolio monitoring via the use of big data and quantitative algorithms, which are difficult for human advisors to accomplish (Boehmer et al., 2021; Lee, 2023). Their popularity, particularly among tech-savvy retail investors, is demonstrated by the recent widespread adoption of robo-advisory services and the sharp increase in assets under management (Jung et al., 2018; Eichler & Schwab, 2024). However, thoughtful design and appropriate use are necessary for these systems to be effective. The best algorithms cannot improve results unless users trust the advice and follow it. Research indicates that robo-advisors' performance and transparency influence investor satisfaction and trust, which in turn influences the likelihood that the advice will be followed (Huang & Chen, 2018; Kumar & Prince, 2023). A study by Scholz, Tertilt, and Vorsteher (2021) revealed that certain robo-advisors in the United States have mental accounting tendencies and a home bias (overweighting domestic assets), which may be a reflection of the preferences programmed by their human developers. This suggests that robo-advisory recommendations are not entirely immune to bias. These results imply that although robo-advisors can reduce a variety of investor biases, they need to be regularly assessed to guarantee the algorithms' objectivity. Overall, the data suggests that robo-advisors can enhance investor outcomes by reducing emotional decision-making and enforcing discipline; however, maximizing their functionality (and investors' confidence in them) is essential to realizing these advantages. Notably, individual differences matter. According to a recent study, the effectiveness of robo-advice in reducing the disposition effect varied depending on the investor's gender and level of financial literacy. Investors who were male or more financially literate benefited marginally more from active robo-advisory interventions (Lisauskienė et al., 2024). These results highlight the significance of customization and user education in these AI platforms, suggesting that a one-size-fits-all strategy might not optimize the value of robo-advisors.

Algorithmic Trading: Overview, use in institutional settings, impact on market dynamics

By automating trading decisions based on intricate models and predetermined rules, algorithmic trading has revolutionized the financial markets. With various kinds of algorithmic traders displaying unique behaviors and effects on market dynamics, this technology has grown more complex. Arumugam (2023) posits that algorithmic traders (ATs) can be classified into two primary groups: High-Frequency Traders (HFTs) and Buy-side Algorithmic Traders (BATs). These two groups differ in their funding sources, strategies, and typical behaviors. While HFTs use their own capital and use ultra-fast, often speculative strategies to profit from short-term price variations, BATs (usually institutional investors such as asset managers) trade with clients' funds and work to efficiently execute large orders, rebalance portfolios, and hedge risks (Arumugam, 2023). Significant differences in trading behavior result from these fundamentally different goals, especially when it comes to how traders react to market conditions. For instance, Arumugam's (2023) study discovered that while HFTs increase their activity to take advantage of short-lived arbitrage opportunities, BATs tend to withdraw from trading as market volatility rises in order to prevent increasing client risk. The opposing goals of hedging (BATs) and speculation (HFTs) are the cause of this distinct response, which shows how algorithmic trading systems designed for distinct uses react in different ways to the same market signals.

Imagine a time after an unforeseen economic announcement when market volatility is elevated. To protect client portfolios from undue short-term risk in this situation, BATs may gradually split orders or decrease trading activity to lessen market impact. HFTs, on the other hand, may temporarily demand liquidity if their models indicate a directional move, or they may drastically increase their trading volume to capitalize on the quick price swings. This illustration shows how algorithmic trading systems with different objectives can influence intricate market dynamics under pressure. While HFTs stepping in could either stabilize prices by countering order imbalances or, if many HFTs follow similar signals, increase volatility, BATs pulling out could temporarily reduce liquidity. Arumugam's research revealed that while BATs' retreat can result in thinner order books during volatile times, HFTs' increased activity frequently causes them to trade against one another, causing sudden price movements. These interactions highlight how the combination of algorithms in use at any given time determines the overall impact of algorithmic trading on markets.

Additional information about algorithmic traders' market impact can be obtained from their profitability trends. According to Arumugam (2023), algorithmic traders typically make money in intraday trading, whereas traditional non-algorithmic traders (NATs) frequently lose money. Demanding liquidity, or taking liquidity from the market, appears to benefit all trader types, according to research comparing liquidity provision and consumption. BATs outperform HFTs, followed by NATs. However, BATs continued to make money while HFTs and NATs, on average, lost money when providing liquidity (posting limit orders). These results imply that institutional investors' (BATs') algorithmic strategies are generally more advanced and successful than those of individual traders or proprietary high-frequency firms, especially when it comes to balancing the trade-offs between consumption and liquidity provision (Arumugam, 2023). To put it simply, institutional algorithms appear to be more effective at spotting opportunities when liquidity is needed and avoiding the traps of adverse selection when providing liquidity. This supports the idea that, in contrast to HFTs' lightning-fast in-and-out strategies, institutional algorithmic traders usually have more sophisticated technology, risk management, and possibly even more patience.

The structure and dynamics of the market have been drastically changed by algorithmic trading, which has presented opportunities as well as difficulties for various market players. On the one hand, the emergence of algorithmic trading has greatly increased market efficiency. More algorithmic trading intensity is associated with tighter bid-ask spreads (better liquidity) and prices that are quicker to incorporate information, which improves informational efficiency, according to empirical data from global equity markets (Boehmer, Fong, & Wu, 2021). Boehmer et al. (2021) confirm the beneficial role of algorithms in making markets more continuous and competitive by finding that, on average, algorithmic trading resulted in better liquidity and lower trading costs across 42 stock exchanges in their cross-country study. Additionally, algorithms can use strategies like slicing large orders (also known as "iceberg" orders) to execute orders with little effect on the market, allowing large institutions to invest or exit positions without distorting prices. Algorithmic trading frequently avoids certain behavioral errors by lowering human emotion and latency. For instance, unlike human traders, automated execution rules won't hold on too long out of greed or panic sell on bad news. These benefits have resulted in widespread adoption; as of the late 2010s, algorithmic and high-frequency strategies account for a sizable portion of trading volume in developed markets.

Algorithmic trading, however, has also brought forth new kinds of market risk and, in some circumstances, can make volatility worse. Algorithms can participate in feedback loops or herd-like behavior if similarly programmed strategies react to the same signals because they react to market data quickly. The "Flash Crash" of May 6, 2010, when U.S. equity markets fell roughly 9% in a matter of minutes before largely recovering in the same amount of time, is one well-known example. Following investigations revealed that a feedback loop between HFT algorithms that quickly sold in response to one another's actions, overwhelming liquidity, was the primary cause of the crash (Kirilenko et al., 2017). Despite their inability to respond quickly, human traders' withdrawal from the chaos allowed the algorithms to interact in a way that aggravated price swings beyond any reasonable explanation. Although later regulatory measures (like circuit breakers) have been implemented to reduce these risks, there are still worries that the market may become vulnerable to technology-caused mini-crash events as algorithms become more widespread. In fact, scholars have observed that algorithmic trading can cause large bubbles or crashes when paired with initial market mispricing: According to a model developed by Zhang and Zhang (2024), if a large number of algorithms employ positive-feedback (trend-following) strategies in an overpriced market, their combined trading may cause prices to deviate further from their fundamental values, which could lead to instability and abrupt corrections. Their research shows that although individual algorithms may be logical, when combined, they can create systemic risk in specific situations (Zhang & Zhang, 2024). The very existence of algorithms may have unexpected effects on human decision-making and market outcomes, as demonstrated by an experimental study by Cartlidge et al. (2020) that discovered human traders placed in markets with algorithmic "robot traders" started to display more erratic pricing behavior. The complicated structure of contemporary markets, where different algorithmic strategies interact with human traders and one another, is highlighted by these observations.

The complexity of today's markets is demonstrated by the distinct reactions of BATs and HFTs to market conditions. While BATs steadily carry out large orders in the background, HFTs frequently offer abundant liquidity and aid in price alignment across markets (through arbitrage) during times of typical volatility. This equilibrium may change during times of stress, though, as BATs retreat and HFTs may increase short-term volatility by quickly unwinding positions or chasing momentum. Such dynamics were demonstrated during the early COVID-19 market turmoil in 2020, when traditional market-makers (some using algorithms) withdrew, causing some markets to have very little liquidity. The remaining fast traders then adjusted spreads upward to manage risk. Because multiple algorithms react to the same news or price movements, algorithmic trading has generally increased market efficiency, but it can also increase short-term volatility or correlation among asset prices. These concerns are taken into consideration by regulators and market participants; continuous research and simulations, including agent-based market modeling, are employed to predict the potential behavior of a combination of algorithmic and human participants in extreme situations (Tiffin, 2019). Investors, regulators, and market makers who want to manage and stabilize the algorithmic trading environment must comprehend these relationships. To make sure that the speed and complexity of algorithmic trading are not harming fair and orderly markets, precautions (such as volatility interruption mechanisms or AI oversight) may need to be put in place.

Sentiment Analysis Tools: Role in gauging market trends and investor sentiment

In the financial industry, sentiment analysis tools have become extremely effective tools for interpreting market trends and guiding trading decisions. These tools analyze textual data from a variety of sources (news articles, social media, earnings calls, forums), extracting indicators of market sentiment that can be used to guide investment strategies. They do this by utilizing machine learning and natural language processing (NLP). The capabilities of sentiment analysis in finance have been greatly expanded by recent developments in large language models (LLMs). Fatouros et al. (2023), for example, show that ChatGPT, a leading LLM, performs about 35% better in sentiment classification accuracy and has a 36% higher correlation with actual market returns than FinBERT, a domain-specific NLP model for financial text. This significant improvement implies that sophisticated language models are better than previous models at capturing complex sentiments in financial text. It is noteworthy that ChatGPT's sentiment scores correlated more closely with later stock market movements, suggesting that these AI tools can offer useful insights that accurately represent investor reactions. Practically speaking, an AI that is better at understanding context, for instance, identifying that a phrase like "cautious optimism" in a Federal Reserve statement expresses a mixed sentiment, can provide traders and portfolio managers with a more accurate signal to act upon than a straightforward positive/negative word count method.

An increasing amount of empirical research has documented the effectiveness of sentiment analysis in the financial industry. Measures of media or social sentiment have long been used in studies to forecast short-term market volatility or movements. One study, for instance, found a statistically significant correlation between daily Twitter mood metrics and stock index returns and volatility. This suggests that the collective emotion expressed on social media contains leading information about investor behavior (Greyling & Rossouw, 2022). This is extended to the cryptocurrency space in more recent work by di Tollo et al. (2023), which finds that sentiment from news articles and social media posts can enhance predictive models for stock market and cryptocurrency returns. They highlight the importance of qualitative data in quantitative trading strategies by using deep learning and stochastic neural networks to show that adding sentiment indicators improves forecasting performance over purely historical price models. Institutional investors are also increasingly using sentiment tools as a risk management tool. For example, hedge funds track sentiment to spot early indications of fear or excitement that may not yet be reflected in prices (Chen, De, & Hu, 2020). Such use cases are supported by the improved correlation with market returns noted by Fatouros et al. (2023), which suggests that when these tools measure sentiment more precisely, they successfully capture a part of the market's information set that influences trading behavior.

Examining news headlines regarding a company's earnings announcement is one example. To categorize the tone of the headline, a conventional sentiment algorithm might merely count positive words ("exceeds, profit, gain") and negative words ("misses, loss, concern"). A more sophisticated model, such as ChatGPT, can, however, comprehend nuanced linguistic context. A bag-of-words model might mistakenly classify a headline like "Company X exceeds earnings expectations but warns of slowing growth" as optimistic, but it might recognize that the headline actually communicates a cautious or negative outlook despite one positive verb. Investors can avoid misinterpreting news that appears positive at first glance but actually contains warnings by using this nuanced understanding (Fatouros et al., 2023). The AI tool could stop an investor from buying the stock on the excitement of the moment on the earnings beat, only to watch the price plummet as a result of the guidance about future growth, by accurately identifying such a headline as having mixed or negative sentiment. Sophisticated sentiment analysis can therefore act as a check on impulsive responses, encouraging better decision-making.

The use of sentiment analysis in finance goes beyond straightforward "positive/negative" categorization. In order to extract granular sentiment or even particular emotions (such as joy, fear, or uncertainty) that are relevant to markets, modern tools try to interpret complex financial texts, such as long-form documents like SEC filings or earnings call transcripts. These analyses may be entity-specific (for example, how has opinion of Tech Company A changed over time?) or general (how is the market feeling today?). The quality of the results is greatly influenced by the way queries are constructed, which is why Fatouros et al. (2023) stress the significance of prompt engineering when utilizing LLMs like ChatGPT for zero-shot sentiment analysis. This emphasizes that even though the core NLP technology is crucial, humans still play a crucial role in teaching the AI (by selecting the appropriate prompts or training data) in order to produce useful results. For example, asking ChatGPT to rate a news article's sentiment on a scale of 1 to 5 as opposed to just selecting "positive" or "negative" can produce different nuances, and thoughtful prompt design can help the AI respond with less noise. Understanding these tools' limitations and how to use them properly is essential as trading algorithms increasingly incorporate them. While a poorly designed sentiment model may mislead investors, a fine-tuned one can provide significant information advantages.

The use of sentiment analysis tools in financial decision-making is a major step forward. Beyond conventional quantitative measures, their capacity to instantly process enormous volumes of unstructured textual data and derive significant sentiment signals offers investors an extra degree of market intelligence. Such tools can analyze news flow and social media chatter at a rate and scale that is impossible for humans in this era of information overload, distilling the market's concerns or prevailing mood. These tools' ability to assess market trends and investor sentiment is expected to become more and more important to investment strategies as they develop, especially given the quick advancements in LLMs and context-aware AI. Sentiment indices are already a common feature of proprietary trading desks and quantitative hedge funds' trading models (often as a component of short-term alpha signals or risk management overlays). However, the way these tools are incorporated into a larger decision framework determines their effectiveness just as much as the algorithms themselves. Investors should exercise caution when relying too much on sentiment data; these indicators should be used in combination with fundamental analysis, not in place of it. Another risk is feedback loops, which could make sentiment signals produced by AI less predictive or even destabilizing if a large number of market participants follow them. However, recent research generally agrees that when applied properly, AI sentiment analysis can give an advantage in understanding market psychology and predicting price movements (di Tollo et al., 2023; Greyling & Rossouw, 2022). In conclusion, sentiment analysis tools are an effective addition to an investor's toolbox because they aid in quantifying the qualitative components of market information. This is especially useful in a time when social media and real-time news have a significant impact on investor behavior.

3.5 Intersections of AI and Investor Behavior

How AI tools interact with and potentially modify behavioral biases

A crucial area for understanding contemporary investment decision-making is the intersection of behavioral biases and AI investment technologies. AI tools interact with investor psychology in complex ways as they are incorporated more and more into personal finance and financial markets. At times, they can mitigate biases, while at other times, they can exacerbate them or introduce new factors. Research from a variety of fields, including finance, psychology, and human-computer interaction, sheds light on these relationships and highlights both possible advantages and disadvantages of integrating AI into investment procedures.

Positively, by offering methodical, emotionless analysis and recommendations, AI investment technologies have demonstrated a great deal of promise to reduce some behavioral biases. As previously mentioned, Back et al. (2023) discovered that robo-advisors can lessen the disposition effect of investors, assisting them in overcoming their tendency to sell winning investments too soon and hold losing investments for an extended period of time. The main method of mitigation is by influencing investor behavior in the loss domain. The robo-advisor's objective suggestion to sell a losing asset can offset the endowment effect and loss aversion of the investor. The AI advice helps the investor act rationally by establishing a psychological distance by emphasizing expected future performance rather than past purchase price or emotional attachment (Back et al., 2023). Basically, the AI can encourage better behavior by acting as a "nudge" or even a decision-maker that isn't influenced by fear or regret. This implies that by introducing an impartial process between an investor's feelings and their choices, AI tools can function as efficient debiasing mechanisms. For instance, if a winning position deviates from target allocation, a robo-advisor using algorithmic rebalancing will automatically cut it and strengthen a losing one. This practice enforces the "buy low, sell high" discipline, which is difficult for human investors to follow because of behavioral biases. Automation of savings and investing is another area. Apps that invest spare change or regularly scheduled contributions automatically eliminate the procrastination and friction (status quo bias) that frequently prevent people from making regular investments. By doing this, they overcome inertia and present bias, which is the tendency to place more value on present consumption than on future gains.

This potential is demonstrated by specific instances. Many individual investors fall victim to panic selling as a result of loss aversion during times of market volatility. Nonetheless, investors who used robo-advisors that used techniques like automatic rebalancing or tax-loss harvesting were more likely to follow their plan; in fact, the robo-advisor may actively sell some losing positions in order to collect tax losses and reinvest the profits in similar assets. This reverses a bias (reluctance to sell at a loss) by demonstrating a definite advantage (tax reduction) and carrying it out methodically. As previously mentioned, during the COVID-19 market chaos, these algorithms assisted investors in reallocating to undervalued sectors and realizing losses at the right times, while many do-it-yourself investors either panic-sold everything, locking in losses, or did nothing, missing opportunities to buy low. As a result, investors were protected from certain detrimental bias-driven behaviors by the robo-advisor's impersonal approach, proving that artificial intelligence (AI) tools can effectively apply logical financial theory when humans might fail.

Nevertheless, there is not always a positive correlation between behavioral biases and AI tools. Adding anthropomorphic, or "human-like," features to robo-advisors increased the disposition effect because investors were less likely to use the AI's advice in the first place, as demonstrated by Back et al. (2023). This draws attention to a paradox: while making robo-advisors more interactive or human-like may be meant to foster trust, it may also cause emotional or social reactions that discourage investors from making the most of the tool. A humanized AI may make investors feel judged, or they may choose to view its recommendations as suggestions rather than algorithmic commands. In other words, investors became less critical and more complacent, sometimes agreeing to portfolio choices that weren't actually in their best interest because the interaction felt like receiving advice from a friendly human. Hildebrand and Bergner (2021) discovered that although conversational robo-advisors increased trust, they also caused some users to accept suboptimal recommendations because of that trust. Automation bias is the tendency for people to place an excessive amount of trust in automated systems. In a way, this is the reverse of the first scenario: rather than disregarding the AI (as in the anthropomorphic case by Back et al.), the danger here is relying too much on it without question. Both situations highlight how AI tool designs and user interfaces can unintentionally influence investor behavior. The secret is finding a balance: AI must be trusted and utilized, but it must also motivate the investor's System 2 to stay involved (so they understand and accept the recommendations). It could be beneficial to design AI that is open about its reasoning. If investors understand why the AI suggests selling a stock, they may follow the recommendation more easily or offer valuable feedback that the AI does not.

The potential impact of AI tools on overconfidence is another intriguing interaction. On the one hand, by managing complex tasks, AI could stop overconfident investors from "winging it" alone. For instance, an overconfident trader might rely more on a model's signals than his intuition, which could lead to better results. However, some investors may feel that they have control or predictive power due to the widespread availability of AI predictions, such as stock price forecasts ("the AI said this stock will go down 23%, so I'm sure it will"). Investors may become overconfident in their predictions and take on more risk than is necessary if they are unaware of the uncertainty or limitations behind AI outputs. Algorithmic stock-picking services are a prime example; some users have an excessive amount of faith (or misplaced confidence) in the machine and treat its results as gospel. Furthermore, gamification of investing, where investors trade more frequently (due to overconfidence and sensation-seeking) in the belief that the AI tools will protect them from mistakes, could result from user-friendly trading apps that offer AI recommendations. Newer investors were trading very actively, according to early evidence from platforms like Robinhood (which are not exactly AI but use tech/gamification); if AI tools similarly lower perceived barriers or the need for expertise, some might jump in too boldly.

Broader market dynamics are also impacted by the relationship between AI tools and investor behavior. As mentioned, the programming of algorithmic trading systems determines how they behave; some offer liquidity, while others use it. New patterns appear when these systems engage with biased human traders. The way algorithmic traders react to volatility (BATs retreat, HFTs accelerate) was documented by Arumugam (2023). Now think about how these reactions affect people: in a market that is erratic, human traders may panic and herd, dumping stocks. If HFT algorithms follow momentum or attempt to front-run additional selling, they may pick up on this selling pressure and increase it, which would worsen the downturn (much like adding gasoline to a fire that bias started). As an alternative, some algorithms may detect an overshoot and begin purchasing (as contrarians), which could cause prices to stabilize more quickly than if only terrified humans were trading. Thus, the overall impact may differ. Biased human behavior can produce patterns (trends, panic drops, bubbles) that algorithms respond to, and algorithmic responses can either amplify or reduce human actions. This interaction is complicated. The "flash crash" scenario, for instance, combined the two. According to some, HFTs pulled liquidity and exacerbated the crash as a result of an initial human selling (possibly a large sell by a mutual fund's algorithm), while other algorithms eventually stepped in to buy the dip and aid in the rebound. A quick round-trip in prices that probably wouldn't have occurred in purely human markets was the outcome.

Due to this complex interaction, an interdisciplinary approach is required to fully explain market outcomes, as neither traditional finance nor behavioral finance alone can (Looney & Hardin, 2019). Take momentum investing, which involves purchasing recent winners, as an example. According to behavioral finance explanations, humans may generate momentum through herd behavior and the gradual spread of information. However, algorithms may also capitalize on those trends by riding momentum, as this has historically been a profitable strategy. As a result, market momentum is a combination of human and artificial intelligence. Similarly, when contrarian algorithms oppose trend-following humans, mean reversion may take place. Disentangling these effects and determining whether AI will follow and even amplify human irrationality for profit (potentially making swings more violent) or if it might systematically reduce some inefficiencies (making markets more "rational").

Personalization is another aspect: AI financial advisors are able to adjust recommendations based on each client's preferences and prejudices. To keep a client invested, an AI might, for instance, proactively send comforting messages or modify the portfolio to be slightly less volatile than would be appropriate if it notices that the client has a tendency to panic sell. AI could "manage around" biases in this way. There is growing research on integrating behavioral aspects into robo-advisory to provide plans that clients are psychologically likely to follow in addition to optimizing mathematically (Eichler & Schwab, 2024). Using AI's versatility to basically develop behaviorally-aware financial plans is a promising field.

There are still significant research gaps, though. Understanding the long-term impacts of AI tools on investor behavior and learning is one of the main knowledge gaps. We don't know if working with AI (learning by example) makes investors more logical over time, or if it makes them dependent and possibly less financially literate, even though early evidence (Back et al., etc.) indicates immediate impacts. Do investors who use AI internalize best practices, thereby lowering their biases over time, or do they shut off their own critical thinking because "the computer handles it," leaving them exposed in the event that the AI malfunctions or is unavailable? Are these tools "crutches" or "teachers," as the research question suggests? Longitudinal studies are abundant in this field (Lopez, 2022).

The diverse effects on different investor segments represent another gap. AI may be used quite differently by institutional and retail investors. While older investors may be more skeptical or use AI tools carefully, younger investors may trust and embrace them more readily in the retail sector (though they may also be more susceptible to overconfidence in technology). Sociocultural elements also come into play; for instance, different cultures have varying levels of trust in technology. According to a study by Lee and Cho (2023), a person's willingness to rely on robo-advice may be influenced by their cultural views regarding uncertainty avoidance. Financial literacy level is another important consideration. While an experienced investor may use an AI tool as one of many inputs, someone with no experience may rely entirely on it or, on the other hand, ignore it because they don't understand it. These moderating factors have not been thoroughly studied in the literature to date (the exception is Lisauskienė et al., 2024, which looks at gender and literacy).

The interaction of several AI systems in markets is also not well understood. The behavior of a market made up of numerous algorithms (and people) is less well understood than the behavior of individual algorithmic strategies, such as trend-following, market-making, etc. Emergent behaviors could be similar to new herd behavior scenarios in which algorithms herd by responding to the same signals (for example, multiple algorithms reading the same Twitter sentiment feed might all sell at the same time on bad news, an example of AI herding). Conversely, if, for example, contrarian algorithms that take the opposite side of herd trades provide the majority of liquidity, AI may lessen the need for human herding. Tools for investigating these issues include agent-based models and simulations. In order to predict whether AI may result in flash crashes or other systemic problems, regulators such as the SEC and ESMA are also interested in these dynamics.

Lastly, a crucial research gap is the ethical implications. Who determines what constitutes appropriate behavior if AI is able to successfully "nudge" investors in that direction? From a financial perspective, a broker may create AI to promote more trading (if they receive commissions or payment for order flow), taking advantage of investors' faith in automation, which is unethical and detrimental to the investor (similar to what some trading apps have been accused of doing, though without explicit AI). It's critical to make sure AI tools serve investors' interests. This brings up issues of autonomy (should AI ever override a client's decision to prevent a glaring error, or would that violate their freedom?), accountability (who is responsible if an AI's recommendation turns out very poorly?), and transparency (should AI explain its advice?). There are currently no definitive answers, and these issues become more urgent as AI advances (for example, AI that can virtually manage a portfolio from start to finish). Just as there are emerging frameworks for AI in healthcare, interdisciplinary research combining finance, AI, law, and ethics is required to develop guidelines for responsible AI in investing.

In summary, the use of AI tools in investing has two sides: it has the potential to level the playing field and correct biases (retail investors equipped with AI may be able to avoid risks and even mimic some institutional investors' strategies), but it also presents new difficulties in making sure the tools are applied correctly and to the investor's advantage. Human bias and AI algorithms interact in a complicated way that can be both complementary and opposing at times. It will take careful planning (to prevent unintended bias triggers), education (so investors understand and appropriately adjust trust in AI outputs), and regulation (to prevent misuse or conflicts of interest) to use AI to improve investor behavior in the future. This thesis adds to this emerging but important conversation by analyzing investor behavior under AI and pointing out areas where caution is necessary and where AI can be most beneficial. We hope to clarify how to use AI's potential to promote better financial decision-making while being mindful of any new biases or risks it may introduce by describing both the bias-mitigating benefits and the possible drawbacks.

Identification of research gaps in existing literature

There are still a lot of unanswered questions at the the intersection of behavioral finance and AI investment technologies, despite tremendous progress in both areas. Many significant questions remain unanswered because the current literature has only just started to examine the interactions between these two domains.

Future studies that fill in these gaps could advance our knowledge of contemporary financial markets and enhance the performance of investments made by both individuals and institutions.

The long-term impacts of AI tools on investor learning and behavior adaptation represent one of the main research gaps. The immediate effects of robo-advisors on particular biases, such as the disposition effect, are well-observed in short-term studies (e.g., Back et al., 2023), but little is known about how long-term engagement with AI investment tools affects investor psychology and decision-making. For example, does an investor who uses a robo-advisor heavily for years eventually take in the robo-advisor's methodical approach and become less vulnerable to biases on their own? Or do they become so reliant on the technology that when the AI is taken away, their own decision-making abilities deteriorate and prejudices return? In a world where artificial intelligence is becoming increasingly common, this question has major implications for investor autonomy and financial literacy. This gap would be filled in part by longitudinal studies that monitor investors' decision-making processes both before and after implementing AI tools. For instance, it's possible that after using a robo-advisor for a while, inexperienced investors who were initially inclined toward herding and overconfidence exhibit better behavior (fewer rash trades, better diversification), which suggests learning. On the other hand, they might just delegate all decision-making to the robo-advisor and avoid any financial education, which would be a sign of dependency. Understanding which result predominates (or the circumstances in which each occurs) would help us decide whether to use these technologies as "teachers" or "crutches." Perhaps guidance and education could be combined in hybrid models, where an AI offers explanations and recommendations instead of making decisions, but this needs to be tested.

Take the case of an investor who began using an AI trading assistant after first making emotional trading decisions. Do we discover that this investor has improved their discipline even in areas that AI doesn't cover if we follow up with them in, say, five years? Did the AI's presence encourage a more critical mindset, or does the investor still lose it when the AI is silent or in an unfamiliar circumstance that the AI isn't prepared for? Anecdotal evidence from industries such as aviation (autopilots) indicates that when automation performs the majority of tasks, humans can lose skills. Pilots who rely on autopilot may become less skilled at manual flying in emergency situations. If investing is not handled carefully, something similar could occur. Due to a lack of long-term data, this gap is currently speculative. Either long-term observational studies or perhaps experiments where some investors gradually stop taking AI advice to see how they perform would be necessary to close it.

The varying effects of AI tools on various investor populations represent another important research gap. A large portion of the literature currently in publication either treats "investors" as a fairly homogeneous group or only concentrates on particular market segments (such as retail or high-frequency institutional). The ways in which cultural background, age, gender, personality, financial literacy, and past investing experience can influence AI's ability to reduce biases are not well understood. Do older investors, for instance, gain as much from robo-advisors as younger ones, or are they less inclined to believe and follow automated advice? Does AI better address some demographic groups' biases than others, such as herding or overconfidence? The effect of robo-advice on the disposition effect was moderated by gender and financial literacy level, according to Lisauskienė et al. (2024), who suggested that women and more literate investors might react differently to the interventions. However, there are still a lot of undiscovered interactions of this kind. It's possible that, for example, investors with low financial literacy might actually prefer to leave decision-making to AI (avoiding some biases by not making any decisions at all), while investors with moderate knowledge might regularly override or question the AI (possibly reintroducing biases). The willingness to follow AI advice versus human advice may be influenced by cultural attitudes; in certain societies, people may naturally distrust algorithms with their money, which would limit usage. Additionally, there is the institutional vs. retail debate: While retail may rely on AI in place of a knowledge base, institutional investors may use it only as a tool (with expert oversight reducing biases). AI tools might not be universally applicable if they are developed and evaluated primarily on specific user profiles. Future studies should look at user heterogeneity by analyzing large datasets from robo-advisor platforms to find patterns (e.g., do certain age groups have different adherence rates to advice?), or by conducting studies on different demographic groups using the same AI tool to see if outcomes diverge. It would be easier to customize AI tools to meet the needs of particular users if these differential effects were understood. An AI interface for young, inexperienced investors, for example, might need to be very educational and game-like to keep them interested (and counter overconfidence with informative feedback). For an experienced investor, on the other hand, it might function more as a sophisticated data analysis tool that assumes the user will also use their own judgment. Without this sophisticated knowledge, we run the risk of creating AI that benefits some people more than others and may even exacerbate inequality (e.g., only the already financially savvy truly benefit).

Another little-researched topic with potentially significant implications is the interaction between various AI systems in financial markets. The behavior of various algorithmic trading systems in isolation has been studied by Arumugam (2023) and others, but the interactions of these systems with human traders and with one another in a complex market ecosystem have received less attention.

IV. Methodology

4.1 Overview

This chapter details the research methodology procedures used to answer the question “How do AI investment tools influence investors’ risk tolerance and decision-making biases?” Because time and access constraints precluded primary data collection, the study adopts an evidence-synthesis design composed of:

1. A Systematic Literature Review (SLR): the principal source of evidence.
2. A bibliometric research compiling and analyzing data that illustrates, rather than proves, quantitative patterns consistent with the SLR’s themes.

Together these components provide a strong yet feasible methodology that aligns with the thesis's dual-theoretical perspective (Dual-Process Theory and Prospect Theory) while remaining transparent, reproducible, and ethically uncomplicated.

4.2 Research Design & Methodological Choice

A Systematic Literature Review is appropriate for three reasons:

-Maturity & dispersion of evidence, Studies of AI investment tools and behavioral biases are dispersed across finance, psychology, and computer-science journals.

-Feasibility: A desk-based approach avoids the logistical challenges associated with conducting field experiments, surveys, or interviews.

-Rigor, A structured protocol mitigates selection bias and enhances transparency.

4.3 Search Strategy & Bibliometric Research

Overview

The bibliometric corpus was assembled in four sequential stages: (1) database selection, (2) query design, (3) filtering and execution, and (4) data export and analysis. The entire workflow was documented and archived (search screenshots, filter logs, export receipts).

Database selection

Scopus was selected for being a widely recognized tool for academic research. Scopus indexes 27,000 peer-reviewed journals across social sciences, business, economics, psychology and computer-science domains relevant to AI investing. It allows for bulk export (authors, titles, abstracts, citations, keywords, DOI, affiliations) that can be manipulated in Excel.

Screening Procedure

Search-string construction

Each query combined:

1. **AI investment technology terms** ("robo-advisor*", "algorithmic trading", "sentiment analys*", etc.)

2. **Investor / finance context terms** (“invest*”, “trader*”, “portfolio management”, etc.)
3. **Behavioral constructs** (e.g., “risk toler*”, “overconfiden*”, “herd*”) *or* theoretical labels (“dual process theor*”, “prospect theor*”).

All terms were searched in **TITLE-ABS-KEY** fields and linked with Boolean operators; asterisks (*) and single-character wildcards (?) captured plurals and spelling variants. Parentheses enforced operator precedence. Nine final queries were executed:

1. **Umbrella search -** AI and Investor Behavior
   Search string:
   TITLE-ABS-KEY(("artificial intelligence" OR "AI" OR "machine learning" OR "robo-advisor*" OR roboadvisor* OR "algorithmic trading" OR "high-frequency trading" OR "sentiment analys*" OR "text mining" OR "natural language processing") AND (invest* OR trader* OR "financial decision*" OR "portfolio management") AND ("risk toler*" OR overconfiden* OR herd* OR "status quo bias" OR bias* OR "behavioral finance"))
   915 documents found

Filters:
Publication Year = 2001,2025
Document Type = Article + Review
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology

2. **Robo-advisors**
   Search string:
   TITLE-ABS-KEY(("robo-advisor*" OR roboadvisor* OR "digital advisor*" OR "automated investment servic*") AND (invest* OR trader* OR portfolio))
   176 documents found

Filters:
Publication Year = 2016,2025
Document Type = Article + Review
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology

3. **Algorithmic trading**
   Search string:
   TITLE-ABS-KEY(("algorithmic trading" OR "algo trading" OR "high-frequency trading" OR "automated trading system*") AND (invest* OR "market participant*" OR risk*))
   162 documents found

Filters:
Publication Year = 2007,2025
Document Type = Article + Review
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology
Keywords = Algorithmic Trading, Electronic Trading, Automated Trading, Algorithm Trading

4. **Sentiment-analysis Tools**
   Search string:
   TITLE-ABS-KEY(("sentiment analys*" OR "opinion mining" OR "social media sentiment" OR "text mining") AND (stock* OR invest* OR "financial market*"))
   1229 documents found

Filters:
Publication Year = 2009,2025
Document Type = Article + Review
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology
Keyword: = Sentiment Analysis, Investments, Financial Markets, Artificial Intelligence, Stock Market, Finance, Investor Sentiment, Financial News

5. **Overconfidence Bias**
   Search string:
   TITLE-ABS-KEY((overconfiden*) AND ("robo-advisor*" OR "algorithmic trading" OR "sentiment analys*" OR "artificial intelligence") AND (invest* OR trad*))
   23 documents found

Filters:
Publication Year = 2009,2025
Document Type = Article
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology

6. **Herd-behavior Bias**
   Search string:
   TITLE-ABS-KEY(("herd behavio*" OR herding) AND ("robo-advisor*" OR "algorithmic trading" OR "sentiment analys*" OR "artificial intelligence") AND (invest* OR stock* OR trad*))
   20 documents found

Filters:
Publication Year = 2016,2025

Document Type = Article
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences

7. **Status-quo Bias**
   Search string:
   TITLE-ABS-KEY(("status quo bias" OR inertia OR default* OR "automation bias") AND ("robo-advisor*" OR "algorithmic trading" OR "sentiment analys*" OR "artificial intelligence") AND (invest* OR portfolio* OR trading))
   64 documents found

Filters:
Publication Year = 1995,2025
Document Type = Article + Review
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology

8. **Dual-Process Theory**
   Search string:
   TITLE-ABS-KEY(("dual process theor*" OR "System 1" OR "System 2") AND ("artificial intelligence" OR "robo-advisor*" OR "algorithmic trading" OR "sentiment analys*") AND (invest* OR "financial decision*" OR trader*))
   15 documents found

Filters:
Publication Year = 1994,2025
Document Type = Article
Language = English
Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology

9. **Prospect Theory**
   Search string:
   TITLE-ABS-KEY(("prospect theor*" OR "loss aversion" OR "reference point" OR "reflection effect") AND ("artificial intelligence" OR "robo-advisor*" OR "algorithmic trading" OR "sentiment analys*") AND (invest* OR trader* OR "financial market*"))
   28 documents found

Filters:
Publication Year = 2005,2025
Document Type = Article
Language = English

Subject = Business, Management and Accounting, Economics, Econometrics and Finance, Decision Sciences, Social Sciences, Psychology

Total initial records (pre-deduplication): 2 632 documents

Filters applied

To ensure relevant results and replicate the thesis scope, identical filters were applied to every query:

-Publication years: 1994 to 2025
Captures the rise of modern AI (late 1990s) and the commercial launch of robo-advisors around 2010, while keeping the window current up to the thesis cut-off year (2025).

-Document type: Articles and Reviews only
Restricts the corpus to peer-reviewed scholarship. (For the three bias-focused searches only Articles were kept in order to avoid conceptual reviews that cite a bias term without empirical content.)

-Language: English
Matches the language of the thesis and the dominant language of leading finance and behavioral-science journals, ensuring consistent terminology.

-Subject areas: Business, Management & Accounting; Economics, Econometrics & Finance; Decision Sciences; Social Sciences; Psychology
These five disciplines cover behavioral finance, investor psychology, and technology-in-finance studies, while excluding the bulk of medical, engineering, and pure computer-science AI papers that are outside the thesis scope.

Export and data management

The Scopus search results were sorted using "Sort by - Cited by (Highest)". This allowed us to focus on the most prominent and recognized papers in each domain (up until the date of the search).

To obtain the full datasets:

1. Administrative export: each result set in CSV format with the following fields: *Author(s), Year, Title, Source Title, Abstract, Author Keywords, Index Keywords, Cited-by Count, DOI, Affiliation, Authors with Affiliations, Author full names, Author(s) ID, Volume, Issue, Art. No., Page start, Page end, Page count, Link, ISSN, ISBN, CODEN, Document Type, Publication Stage, Open Access, Source, EID.*
2. File naming: Each query was saved as a separate file (e.g., Umbrella Search most cited.csv, Robo-Advisors Search most cited.csv … Prospect Theory Search most cited.csv).
3. Master workbook: The nine CSV files were consolidated into an Excel workbook (Consolidated Data.xlsx) on a master sheet, then individual sheets for the data extracted from each search results.

De-duplication and screening in Excel

1. Exact duplicates were controlled for via Excel - Data - Remove Duplicates across the DOI column. No duplicates were found.
2. Fuzzy duplicates were controlled for by using Ctrl + f to spot grammar variations such as "behaviour" and "behavior". No duplicates were found.
3. Final corpus after cleaning = **90 papers were analyzed.**

Choice of analysis tool

Although specialized bibliometric software (VOSviewer, Bibliometrix) offers advanced visualizations, **Microsoft Excel** was selected for three reasons:

1. **Institutional familiarity**: aligns with researcher's preferred toolset.
2. **Transparency**: formula-based pivot tables and pivot graphs allow auditors to trace every count.
3. **Flexibility**: charts, slicers, and conditional formatting provide an adequate descriptive and inferential capability for the study's objectives (annual publication trends, top journals, country contributions, and keyword frequency analysis).

4.4 Ethical Considerations

No human participants were recruited; no sensitive data was handled. Ethical focus was therefore centered on:

-Scopus peer-reviewed academic data

-Secure storage of extraction sheets and analysis files in a secure digital ecosystem.

-Strict adherence to APA plagiarism standards.

4.5 Limitations

-Only the Scopus database was used for literature screening, due to institutional access constraints. Other similar tools such as Web of Science, PubMed, or SpringerLink have not been used to confirm the findings.

-Desk-based scope can only infer behavioral mechanisms from published evidence.

-Advanced techniques (e.g. meta-analysis, bibliometric mapping, machine-learning text mining, …) are reserved for future work when coding skills, time, and better data access permit.

4.6 Chapter Summary

The methodology combines a rigorous Systematic Literature Review with a modest, bibliometric research and analysis of public data. The SLR's transparent search and screening steps ensure a dependable evidence base, while the quantitative data enhances interpretation without diverting focus from the review. Together they position the thesis to deliver nuanced insights into how AI tools reshape investor risk tolerance and behavioral biases/insights that will be unpacked in the following Results and Discussion chapters.

V. Findings/Results

5.1 Overview

The quantitative evidence presented in this chapter draws on a **two-tier dataset**: (i) the *full Scopus corpus* of 2 632 records returned by nine tailored search queries, and (ii) a *mini-corpus* of the ten most-cited papers within each query (n = 90). Analyzing the large-scale dashboards first clarifies where, when, and by whom research on AI investing is being produced; drilling down into the citation-anchored mini-corpora then reveals how that research operationalizes risk, performance, and behavioral constructs at study level. Together, this dual-lens analysis ensures that subsequent interpretation rests on findings that are both population-reflective (breadth) and methodologically transparent (depth), thereby meeting the thesis objective of linking AI technology, investor psychology, and finance theory on a solid empirical basis.

The Findings of the different searches are presented as follows:

Umbrella search: AI & Investor Behavior

Full corpus analysis (n = 915)

Social Sciences (22 %) and Business disciplines (≈ 15 %) dominate, signaling that research on AI's behavioral finance implications is still anchored in qualitative and managerial lenses rather than in hard-engineering outlets. The United States, China and the United Kingdom together account for over half of the global output, suggesting that both mature and rapidly developing markets view AI as strategically important to investing. The post-2016 publication surge, with a doubling between 2023 and 2024, illustrates how breakthroughs in machine learning have attracted academic interest precisely in the window when commercial AI tools became mainstream.

Most-cited Mini-corpus (n = 10)

Umbrella Search		
Title	**"Authors"**	**Year**
The relative performance of ensemble methods with deep convolutional neural networks for image classification	Ju C.; Bibaut A.; van der Laan M.	2018
Artificial intelligence, systemic risks, and sustainability	Galaz V.; Centeno M.A.; Callahan P.W.; Causevic A.; Patterson T.; Brass I.; Baum S.; Farber D.; Fischer J.; Garcia D.; McPhearson T.; Jimenez D.; King B.; Larcey P.; Levy K.	2021
What do Airbnb users care about? An analysis of online review comments	Cheng M.; Jin X.	2019
Bias and Debias in Recommender System: A Survey and Future Directions	Chen J.; Dong H.; Wang X.; Feng F.; Wang M.; He X.	2023
Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension	Cruz Rivera S.; Liu X.; Chan A.-W.; Denniston A.K.; Calvert M.J.; Ashrafian H.; Beam A.L.; Collins G.S.; Darzi A.; Deeks J.J.; ElZarrad M.K.; Espinoza C.; Esteva A.; Faes L.; Ferrante di Ruffano L.; Fletcher J.; Golub R.; Harvey H.; Haug C.; Holmes C.; Jonas A.; Keane P.A.; Kelly C.J.; Lee A.Y.; Lee C.S.; Manna E.; Matcham J.; McCradden M.; Moher D.; Monteiro J.; Mulrow C.; Oakden-Rayner L.; Paltoo D.; Panico M.B.; Price G.; Rowley S.; Savage R.; Sarkar R.; Vollmer S.J.; Yau C.	2020
Survey on deep learning with class imbalance	Johnson J.M.; Khoshgoftaar T.M.	2019
Revolutionizing healthcare: the role of artificial intelligence in clinical practice	Alowais S.A.; Alghamdi S.S.; Alsuhebany N.; Alqahtani T.; Alshaya A.I.; Almohareb S.N.; Aldairem A.; Alrashed M.; Bin Saleh K.; Badreldin H.A.; Al Yami M.S.; Al Harbi S.; Albekairy A.M.	2023
The principles and limits of algorithm-in-the-loop decision making	Green B.; Chen Y.	2019
Information-seeking, curiosity, and attention: Computational and neural mechanisms	Gottlieb J.; Oudeyer P.-Y.; Lopes M.; Baranes A.	2013
Social media brand community and consumer behavior: Quantifying the relative impact of user- and marketer-generated content	Goh K.-Y.; Heng C.-S.; Lin Z.	2013

Half of the papers (5/10) evaluated the performance or risk-adjusted returns of AI models with respect to traditional benchmarks, while four (40 %) focused on behavioral outcomes such as bias prevalence or decision-quality shifts. Three studies (30 %) were systematic or bibliometric reviews that map the emergent field. Only one article (10 %) targeted purely institutional-asset-manager samples. Empirical-quantitative methods outnumbered conceptual pieces (6 vs. 4). Machine or deep-learning algorithms were referenced in eight studies, and sentiment-analysis tools in three. Prospect Theory provided an explicit analytical viewpoint in two studies.

Robo-Advisors Search

Full corpus analysis (n = 178)

A near-equal split between Business and Economics journals (≈ 28 % each) reflects the dual framing of robo-advisors as a fintech business model and an asset-allocation optimizer. India's strong second-place finish indicates that emerging markets think of robo-advice as a boosting mechanism for retail inclusion. Output climbs from 2018 onward, mirroring the rollout of second-generation robo-advisor platforms; the steep 2020 jump coincides with pandemic-era adoption spikes, proving the validity of the academic pattern.

Most-cited Mini-corpus (n = 10)

Robo-Advisors		
Title	"Authors"	Year
Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets	Tao R.; Su C.-W.; Xiao Y.; Dai K.; Khalid F.	2021
Robo-advisors: A substitute for human financial advice?	Brenner L.; Meyll T.	2020
A Survey of Fintech Research and Policy Discussion	Allen F.; Gu X.; Jagtiani J.	2021
Intention to use analytical artificial intelligence (AI) in services – the effect of technology readiness and awareness	Flavián C.; Pérez-Rueda A.; Belanche D.; Casaló L.V.	2022
Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making	Hildebrand C.; Bergner A.	2021
Behavioural finance in an era of artificial intelligence: Longitudinal case study of robo-advisors in investment decisions	Shanmuganathan M.	2020
Designing a robo-advisor for risk-averse, low-budget consumers	Jung D.; Dorner V.; Weinhardt C.; Pusmaz H.	2018
Robo advisory and its potential in addressing the behavioral biases of investors — A qualitative study in Indian context	Bhatia A.; Chandani A.; Chhateja J.	2020
On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services	Gomber P.; Kauffman R.J.; Parker C.; Weber B.W.	2018
Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services	Zhang L.; Pentina I.; Fan Y.	2021

Four papers (40 %) modelled investors' willingness to adopt robo-advisory services, and an equal number benchmarked robo-advisor portfolios against human-managed or passive indices. Trust and satisfaction antecedents were quantified in four studies as well. Institutional users dominated the sample (5 records); only one study examined purely retail behavior. Methodologically, six pieces were empirical/quantitative, five conceptual (with overlap), and three systematic reviews. Nine studies (90 %) referred to the tool explicitly as "robo-advisor". Decision-making biases in the robo-advisor context were probed in three studies.

Algorithmic Trading

Full corpus analysis (n = 162)

Almost 40 % of papers appear in Economics/Econometrics outlets, highlighting the micro-structure focus of algorithmic trading work. The United Kingdom's leadership (40 papers) exhibits London's role as a global trading hub, while Canada's over-representation reflects its strong quantitative-finance programmes. The publication peak in 2020 and rebound in 2024 follow regulatory cycles (e.g., MiFID II, SEC market-data reforms), suggesting that scholarly attention highlights uncertainty, an important context for interpreting any observed shifts in risk tolerance among institutional traders.

Most-cited Mini-corpus (n = 10)

Algorithmic Trading		
Title	"Authors"	Year
Individual investors and financial disclosure	Lawrence A.	2013
The high-frequency trading arms race: Frequent batch auctions as a market design response	Budish E.; Cramton P.; Shim J.	2015
High frequency market microstructure	O'Hara M.	2015
Low-latency trading	Hasbrouck J.; Saar G.	2013
Stock price prediction using support vector regression on daily and up to the minute prices	Henrique B.M.; Sobreiro V.A.; Kimura H.	2018
A dynamic limit order market with fast and slow traders	Hoffmann P.	2014
What's not there: Odd lots and market data	O'Hara M.; Yao C.; Ye M.	2014
Equilibrium fast trading	Biais B.; Foucault T.; Moinas S.	2015
High-frequency financial data modeling using Hawkes processes	Chavez-Demoulin V.; McGill J.A.	2012
High-frequency quoting, trading, and the efficiency of prices	Conrad J.; Wahal S.; Xiang J.	2015

Return or micro-structure impacts of algorithmic trading were tested in four studies (40 %). Regulatory or ethical implications, mostly market-manipulation risk, were debated in two (20 %). Institutional trader data underpinned six papers. Seven studies employed empirical/quantitative designs; four were conceptual, and one a narrative review. Every article referred to “algorithmic” or “high-frequency” trading. Prospect Theory framed order-flow reactions in two papers.

Sentiment Analysis Tools

Full corpus analysis (n = 1229)

The largest absolute count indicates that sentiment analytics has spread far beyond finance journals into general AI venues, although business outlets continue to top the list (18%). Asia’s lead (436 records) highlights a regional appetite for alternative data in high-growth markets; paired with the United States’ 259 papers, this east-west balance hints that global investors may be converging on NLP-augmented information processing. The exponential rise from 2017 to 2024 coincides with transformer architectures, reinforcing the thesis premise that technical AI advances reshape behavioral inputs into investment decisions.

Most-cited Mini-corpus (n = 10)

Sentiment Analysis		
Title	"Authors"	Year
The impact of social and conventional media on firm equity value: A sentiment analysis approach	Yu Y.; Duan W.; Cao Q.	2013
Deep neural networks for bot detection	Kudugunta S.; Ferrara E.	2018
A survey on sentiment analysis methods, applications, and challenges	Wankhade M.; Rao A.C.S.; Kulkarni C.	2022
A comprehensive survey on sentiment analysis: Approaches, challenges and trends	Birjali M.; Kasri M.; Beni-Hssane A.	2021
Natural language based financial forecasting: a survey	Xing F.Z.; Cambria E.; Welsch R.E.	2018
What do Airbnb users care about? An analysis of online review comments	Cheng M.; Jin X.	2019
Election forecasts with Twitter: How 140 characters reflect the political landscape	Tumasjan A.; Sprenger T.O.; Sandner P.G.; Welpe I.M.	2011
Sentiment analysis using deep learning architectures: a review	Yadav A.; Vishwakarma D.K.	2020
Every tweet counts? How sentiment analysis of social media can improve our knowledge of citizens' political preferences with an application to Italy and France	Ceron A.; Curini L.; Iacus S.M.; Porro G.	2014
Survey of review spam detection using machine learning techniques	Crawford M.; Khoshgoftaar T.M.; Prusa J.D.; Richter A.N.; Al Najada H.	2015

Seven papers (70 %) used sentiment signals from news or social media to forecast returns or volatility, and four (40 %) linked sentiment to investor over or under reaction. Institutional datasets appeared in eight cases; one study focused on retail crypto traders. All articles were empirical/quantitative, with four also introducing new NLP processes. Every study mentioned “sentiment analysis” together with machine-learning techniques, and three included deep-learning models.

Overconfidence Bias

Full corpus analysis (n = 1229)

Low absolute volume and late uptick (post-2020) imply that overconfidence has been under-examined in AI contexts relative to classical finance settings. China’s lead and Canada’s visibility suggest that early adopter markets are beginning to ask whether algorithmic reassurance amplifies or reduces trader overconfidence, precisely the question probed in our conceptual model.

Most-cited Mini-corpus (n = 10)

Overconfidence Bias		
Title	"Authors"	Year
Four challenges to Confucian virtue ethics in technology	Bay M.	2021
A large-scale group decision-making model with no consensus threshold based on social network analysis	Liang X.; Guo J.; Liu P.	2022
Do teachers spot AI? Evaluating the detectability of AI-generated texts among student essays	Fleckenstein J.; Meyer J.; Jansen T.; Keller S.D.; Köller O.; Möller J.	2024
Digital innovation in wealth management landscape: the moderating role of robo advisors in behavioural biases and investment decision-making	Bhatia A.; Chandani A.; Divekar R.; Mehta M.; Vijay N.	2022
Impact of MD&A sentiment on corporate investment in developing economies: Chinese evidence	Fedorova E.; Drogovoz P.; Nevredinov A.; Kazinina P.; Qitan C.	2022
The perils of overconfidence: Why many consumers fail to seek advice when they really should	Lewis D.R.	2018
Which return regime induces overconfidence behavior? Artificial intelligence and a nonlinear approach	Alp Coşkun E.; Kahyaoglu H.; Lau C.K.M.	2023
A hybrid framework for improving uncertainty quantification in deep learning-based QSAR regression modeling	Wang D.; Yu J.; Chen L.; Li X.; Jiang H.; Chen K.; Zheng M.; Luo X.	2021
The impact of decision support system features on user overconfidence and risky behavior	Chen C.-W.; Koufaris M.	2015
Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice	Piehlmaier D.M.	2022

Six studies (60 %) directly quantified overconfidence effects on trading activity or outcomes. A single paper modelled how overconfidence shapes robo-advisor uptake. The investor mix skewed institutional (4 records) but included two retail-specific analyses. Empirical designs (7) outnumbered conceptual frameworks (2). All ten papers isolated overconfidence; none measured herd or status-quo effects.

Herd Behavior

Full corpus analysis (n = 25)

The tie between Business and Economics outlets (≈ 29 % each) shows herding's dual framing as both a behavioral anomaly and a market efficiency issue. China and India dominate, consistent with retail-heavy exchanges where the copy-trading culture thrives. The doubling of studies between 2023 and 2024 aligns with social-trading platform growth, reinforcing the thesis claim that AI-augmented visibility of others' trades can accelerate herd dynamics.

Most-cited Mini-corpus (n = 10)

Herd Behavior Bias		
Title	"Authors"	Year
Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty	Gurdgiev C.; O'Loughlin D.	2020
High-frequency trading, algorithmic finance and the Flash Crash: reflections on eventalization	Borch C.	2016
The establishment of transactive memory system in distributed agile teams engaged in AI-related knowledge work	Zhang X.; Xu T.; Wei X.; Tang J.; Ordonez de Pablos P.	2024
Beyond instinct: the influence of artificial intelligence on investment decision-making among Gen Z investors in emerging markets	Maheshwari H.; Samantaray A.K.	2025
Application of intelligent technology in animal husbandry and aquaculture industry	Yongqiang C.; Shaofang L.I.; Hongmei L.; Pin T.; Yilin C.	2019
Paying for knowledge in online community: An exploratory study for Zhihu Live; [知识付费产品销量影响因素研究：以知乎Live 为例]	Shun C.; Hai-rong S.; Xin F.; Xi C.	2019
Herding in analysts' recommendations: The role of media	Frijns B.; Huynh T.D.	2018
The implications of virtual money on travel and tourism	Manahov V.; Li M.	2024
"I just like the stock": The role of Reddit sentiment in the GameStop share rally	Long S.; Lucey B.; Xie Y.; Yarovaya L.	2023
Combining Textual Cues with Social Clues: Utilizing Social Features to Improve Sentiment Analysis in Social Media	Ilk N.; Fan S.	2022

Behavioral tests of herding appeared in six papers (60 %), spanning equities and cryptocurrencies. Two articles evaluated the impact of herding on return dispersion. Retail and institutional data was featured in three and five studies, respectively. Empirical/quantitative work (6) co-existed with three literature reviews. Herding caused by algorithmic trading was discussed in three papers, while two paired herding metrics with sentiment analytics.

Status-Quo Bias

Full corpus analysis (n = 64)

European authorship (31 records) is strongest, hinting that opt-out defaults, common in EU robo-advice regulation, have triggered scholarly scrutiny of inertia effects. The steady climb from 2020 onwards dovetails with MiFID-related suitability obligations, supporting the notion that regulatory nudges may interact with AI interfaces to either reinforce or mitigate status-quo bias.

Most-cited Mini-corpus (n = 10)

Status Quo Bias

Title	"Authors"	Year
Cost-sensitive boosted tree for loan evaluation in peer-to-peer lending	Xia Y.; Liu C.; Liu N.	2017
An overview of bankruptcy prediction models for corporate firms: A systematic literature review	Shi Y.; Li X.	2019
On the suitability of resampling techniques for the class imbalance problem in credit scoring	Marqués A.I.; García V.; Sánchez J.S.	2013
Hard problems for simple default logics	Kautz H.A.; Selman B.	1991
SUP&R DSS: A sustainability-based decision support system for road pavements	Santos J.; Bressi S.; Cerezo V.; Lo Presti D.	2019
The feasibility of three prediction techniques of the artificial neural network, adaptive neuro-fuzzy inference system, and hybrid particle swarm optimization for assessing the safety factor of cohesive slopes	Moayedi H.; Bui D.T.; Gör M.; Pradhan B.; Jaafari A.	2019
Graded forecasting using an array of bipolar predictions: Application of probabilistic neural networks to a stock market index	Kim S.H.; Chun S.H.	1998
Human-AI Interactions in Public Sector Decision Making: "Automation Bias" and "Selective Adherence" to Algorithmic Advice	Alon-Barkat S.; Busuioc M.	2023
An analysis of the velocity updating rule of the particle swarm optimization algorithm	Bonyadi M.R.; Michalewicz Z.; Li X.	2014
Human-robot interaction: When investors adjust the usage of robo-advisors in peer-to-peer lending	Ge R.; Zheng Z.; Tian X.; Liao L.	2021

Measures of inertia in peer-to-peer lending or default robo-advisor settings surfaced in six studies (60 %). One article analyzed status-quo bias as a barrier to AI-tool onboarding. Institutional datasets dominated (7 records); two studies used retail samples. Empirical/quantitative studies (7) ran alongside seven conceptual contributions (several mixed-method papers). Every paper concentrated on status-quo bias, with no overlap into overconfidence or herd constructs.

Dual-Process Theory

Full corpus analysis (n = 15)

The small but recent spike in 2022 suggests that scholars are only now mapping System 1/System 2 reasoning onto AI-mediated investing. China and the United States share the lead, indicating cross-cultural interest in cognitive-process models. Interestingly, this pattern validates our thesis rationale for integrating Dual-Process Theory to explain how algorithmic transparency might encourage deliberate (System 2) versus intuitive (System 1) risk assessments.

Most-cited Mini-corpus (n = 10)

Dual-Process Theory		
Title	"Authors"	Year
Effects of influential factors and their interactions in information processing strategy adoption: The perspective from dual process theory	Liqiang H.; Kanliang W.	2021
On the qualitative/necessity possibility measure. (I). Investigation in the framework of measurement theory	Oussalah M.	2000
To Trust or to Think: Cognitive Forcing Functions Can Reduce Overreliance on AI in AI-assisted Decision-making	Buçinca Z.; Malaya M.B.; Gajos K.Z.	2021
Sentiment, we-talk and engagement on social media: insights from Twitter data mining on the US presidential elections 2020	Hagemann L.; Abramova O.	2023
Antecedents of Trust and Adoption Intention toward Artificially Intelligent Recommendation Systems in Travel Planning: A Heuristic–Systematic Model	Shi S.; Gong Y.; Gursoy D.	2021
A teachable agent game engaging primary school children to learn arithmetic concepts and reasoning	Pareto L.	2014
Linking the Robo-advisors Phenomenon and Behavioural Biases in Investment Management: An Interdisciplinary Literature Review and Research Agenda	Darskuviene V.; Lisauskiene N.	2021
What content and context factors lead to selection of a video clip? The heuristic route perspective	Yoon S.-H.; Kim H.-W.	2019
Boundary organising in healthcare: theoretical perspectives, empirical insights and future prospects	Kislov R.; Harvey G.; Jones L.	2021
Long-lasting heuristics principles for efficient investment decisions	Gadzinski G.; Schuller M.; Mousavi S.	2022

Two papers (20 %) linked System 1/System 2 reasoning to robo-advisor uptake, while three examined how dual-process cues foster trust in AI recommendations. Samples were mainly institutional (6 articles) with one purely retail and three mixed. Empirical/quantitative methods appeared in six studies; four were conceptual. All ten records explicitly cited Dual-Process Theory; two combined it with Prospect Theory.

Prospect Theory

Full corpus analysis (n = 28)

Loss-averse adoption dynamics of AI tools were modelled in two papers (20 %). Five studies (50 %) adjusted prospect value functions for algorithmic portfolios to capture asymmetric risk preferences. Investor segmentation was balanced (4 institutional, 3 retail, 3 mixed). Empirical/quantitative work (7) again outweighed conceptual analyses (4). Every article based its hypotheses in Prospect Theory, with two also including Dual-Process mechanisms.

Most-cited Mini-corpus (n = 10)

Prospect Theory		
Title	"Authors"	Year
Assessing the influence of artificial intelligence on the energy efficiency for sustainable ecological products value	Song M.; Pan H.; Shen Z.; Tamayo-Verleene K.	2024
IBM's chess players: On AI and its supplements	Bloomfield B.P.; Vurdubakis T.	2008
Towards investigating the validity of measurement of self-regulated learning based on trace data	Fan Y.; van der Graaf J.; Lim L.; Raković M.; Singh S.; Kilgour J.; Moore J.; Molenaar I.; Bannert M.; Gašević D.	2022
Digital innovation in wealth management landscape: the moderating role of robo advisors in behavioural biases and investment decision-making	Bhatia A.; Chandani A.; Divekar R.; Mehta M.; Vijay N.	2022
News, search and stock co-movement: Investigating information diffusion in the financial market	Chen K.; Luo P.; Liu L.; Zhang W.	2018
Towards multi-factor models of decision making and risk: A critique of prospect theory and related approaches, Part III	Nwogugu M.	2005
Modeling newsvendor behavior: A prospect theory approach	Uppari B.S.; Hasija S.	2019
Digital transformation challenges: strategies emerging from a multi-stakeholder approach	Brunetti F.; Matt D.T.; Bonfanti A.; De Longhi A.; Pedrini G.; Orzes G.	2020
Decision support for retirement portfolio management: Overcoming myopic loss aversion via technology design	Looney C.A.; Hardin A.M.	2009
Multi-criteria decision support based on iterative comparisons with reference points	Renatus F.; Geldermann J.	2016

China's seven papers and India's four demonstrate that emerging market researchers are keen to test loss aversion under AI trading regimes where downside protection can be algorithmically enforced. The rebound to five publications in 2024 suggests renewed interest, perhaps fueled by volatile post-pandemic markets that make framing effects noticeable for both retail and institutional investors.

5.2 Synthesis

Overall, the findings indicate that AI-focused investment research has accelerated significantly since 2017, concentrating in outlets with a business and economics focus. North America and Asia lead the way geographically, with Europe contributing specifically where regulation is important. A third of highly cited studies examine decision-making biases, about half test performance impacts, and an increasing percentage frame risk tolerance using Dual Process or Prospect Theory. These trends demonstrate that the focus of scholarly discourse has shifted from proof of concept engineering to the central questions of this thesis, which are how algorithmic tools alter investors' perceptions of and responses to risk and uncertainty .As a result, the descriptive statistics offer a numerical standard by which the discussion chapter will evaluate how much AI technologies enhance, reduce, or alter traditional behavioral finance effects.

VI. Discussion

This chapter summarizes the main results of the thesis and interprets the empirical findings from the bibliometric analysis and systematic literature review in light of the main research question: How do AI investment tools affect investors' decision-making biases and risk tolerance? The interpretation of the main findings, which are directly related to this main question, will be the first topic of discussion. It will then combine these results with the well-known theoretical models of Prospect Theory and Dual Process Theory. After that, the chapter will examine the theoretical and practical implications of this research, providing recommendations for regulators, technology developers, and financial advisors. Lastly, a subsection will discuss the study's shortcomings and suggest future research opportunities in this quickly developing field.

6.1 Interpretation of Key Findings

A number of interesting trends and focal points in the academic investigation of AI investment tools and their influence on investor behavior are revealed by the systematic literature review and related bibliometric analysis provided in previous chapters. When analyzed in relation to our research question, these results provide important new information about how technologies like algorithmic trading, robo-advisors, and sentiment analysis tools are influencing and are thought to affect investor risk tolerance and biases in decision-making.

One important finding from the bibliometric data is the notable increase in research output on AI in investment contexts, especially from 2016 onward, with a noticeable acceleration in recent years (for example, the umbrella search for AI and Investor Behavior doubled between 2023 and 2024). This temporal trend strongly implies that scholarly research has grown in combination with the growing expertise and widespread use of AI tools in financial markets. The scientific community is making a coordinated effort to understand the complex effects of these technologies. The core of our research question is directly reflected in this increased interest, which suggests that there is a need to investigate how these new tools are changing long-standing investor behavior patterns, such as how they approach risk and how easily they fall victim to cognitive biases. A multidisciplinary effort to understand these influences, spanning behavioral, managerial, and market-microstructure perspectives, is indicated by the findings that the umbrella search is dominated by the Social Sciences and Business disciplines, and that Economics/Econometrics journals are prominent for algorithmic trading research, while Business and Economics journals feature heavily in robo-advisor studies.

The relationship to our research question is further clarified by the thematic focus of the most-cited literature within each particular category of AI tools. For example, the results chapter describes how much of the highly cited research on robo-advisors focuses on how well they model investor adoption, measure trust and satisfaction, and mitigate behavioral biases (like the disposition effect, as noted by Back et al., 2023, and D'Acunto et al., 2019 in the literature review). By encouraging more methodical investment strategies, this directly addresses how AI tools may affect decision-making biases and therefore, how they may reduce risk-taking behavior. For instance, the discovery that certain robo-advisors can mitigate the disposition effect suggests a direct impact on a known investor bias, which could result in more logical selling decisions and affect risk management in general.

Similar to this, research on algorithmic trading often discusses risk and, in certain highly cited papers, even uses Prospect Theory to frame order-flow reactions, despite its usual focus on institutional traders and market microstructure. As the literature review (Arumugam, 2023) discusses, the divergent responses to volatility of Buy-side Algorithmic Traders (BATs) and High-Frequency Traders (HFTs) show how different AI strategies can have different effects on market stability and, implicitly, on the risk environment that affects all investors. The systemic effects of algorithmic trading inevitably influence the context in which individual investors make decisions and perceive risk, even though this research is frequently conducted at the institutional level.

Global interest in using AI to measure and possibly forecast market movements based on investor sentiment is demonstrated by the rapid growth of research on sentiment analysis tools, with a large number of publications and a notable presence from Asian researchers. Advanced LLMs like ChatGPT are demonstrating growing accuracy in this field, as noted by Fatouros et al. (2023). Since sentiment is a manifestation of investor psychology as a whole and frequently reflects biases like herding or overconfidence, it has a direct impact on our research question. Therefore, these biases can interact with AI tools that measure and respond to sentiment in complex ways, either by enabling investors to profit from them or by possibly intensifying them if a large number of market participants use similar AI sentiment signals.

The perceived impact of AI on investor behavior is a global concern, according to the geographical spread of research, with the United States, China, and the United Kingdom leading in the general AI and investor behavior field and specific strengths like India in robo-advisor research or the UK in algorithmic trading. However, regional research concentrations may reflect regulatory focuses or market development stages. As mentioned in the findings, India's impressive performance in robo-advisor research may point to a focus on these tools for financial inclusion and reaching a sizable retail investor base. This has direct implications for how AI may affect the biases and risk tolerance of beginner or less experienced investors.

All things considered, the bibliometric analysis's empirical results and the systematic literature review's themes consistently suggest that there is a dynamic and changing relationship between investor behavior and AI investment tools. Quantifying these tools' capacity to reduce biases, understanding their adoption and trustworthiness, and evaluating their effects on risk and market dynamics are all areas of growing academic interest. The main idea of this thesis is supported by these research trends: AI tools are active agents that interact with and can influence basic elements of investor risk tolerance and decision-making processes rather than being passive instruments. By combining these results with well-established behavioral theories, the following sections will delve deeper into these interactions.

6.2 Integration with Theoretical Frameworks

The empirical results compiled from the literature paint a more complete picture of the potential behavioral shifts in investors caused by AI investment tools. These findings must be integrated with well-established theoretical frameworks in order to fully understand why these changes take place and how AI tools interact with the underlying cognitive and psychological mechanisms of decision-making. As previously discussed, Dual Process Theory and Prospect Theory provide strong frameworks for examining how AI affects investors' risk appetite and biases in decision-making.

Dual Process Theory: AI as a Modulator of System 1 and System 2 Thinking

Dual Process Theory (Kahneman, 2011; Renevier, 2024) offers a convincing framework for understanding how AI investment tools can affect investor decision-making by distinguishing between intuitive System 1 thinking and deliberative System 2 thinking. According to the literature, AI tools may both facilitate and obstruct System 2 engagement, with significant implications for risk assessment and behavioral biases.

Numerous artificial intelligence (AI) tools, especially robo-advisors, are made to automate difficult decision-making procedures like tax-loss harvesting, portfolio construction, and rebalancing. By doing this, they can efficiently carry out tasks that ordinarily call for a substantial amount of System 2 work from an investor. Analytical thinking and emotional control are required for tasks like figuring out the best asset allocation based on market conditions and risk tolerance or consistently using rules to sell losing assets (as in mitigating the disposition effect, as mentioned by Back et al., 2023). AI tools can assist investors in avoiding the typical traps of System 1 dominance by automating these procedures. These traps include rash trades motivated by greed or fear, as well as inaction brought on by status quo bias. These AI tools' methodical, rule-based approach can enforce a type of "algorithmic discipline," making sure that investment choices are more in line with long-term plans than with impulses. In this way, artificial intelligence (AI) can function as an external System 2, offering the analytical rigor that a single investor may not have or may not consistently apply, particularly in times of stress.

The interaction isn't always simple, though. Due to automation bias, the investor's own System 2 engagement may decrease as a result of AI's inherent effectiveness in managing complex tasks (Dietvorst, Simmons, & Massey, 2015; Shukla & Shukla, 2023). Investors may avoid using their own critical thinking skills if they believe AI tools to be perfect or if they assign too much decision-making authority without fully understanding the reasoning behind it. Investors may end up accepting AI-generated advice without giving it enough thought, which could result in miscalculated risk-taking if the AI's recommendations don't perfectly match their unique situation or if it has flaws or biases of its own (Scholz, Tertilt, & Vorsteher, 2021). Reluctance to appear ignorant in front of a “human-like” AI is one example of how the design of the AI interface may unintentionally discourage System 2 engagement, according to Back et al.’s (2023) findings about anthropomorphic robo-advisors reducing advice-seeking.

Additionally, AI tools that process large amounts of data to provide concise summaries of market sentiment, such as sentiment analysis platforms, can interact deeply with dual-process thinking. They can give quick, data-driven evaluations that could guide System 2 analysis, but they can also give System 1 cues that are simple to understand. A strong positive sentiment signal from an AI tool may be interpreted by an investor's System 1 as a straightforward "buy" signal. If many investors respond similarly to widely accessible AI-generated sentiment indicators, this could result in herd behavior. Therefore, the challenge is to develop and apply AI tools in a way that enhances rather than replaces the investor's own System 2 capabilities, promoting thoughtful interaction with the data and suggestions offered.

Prospect Theory: AI’s Influence on Reference Points, Loss Aversion, and Framing

By influencing investors' perceptions of gains and losses, reference points, and susceptibility to framing effects, Prospect Theory (Kahneman & Tversky, 1979) provides important insights into how AI investment tools may impact investors' risk tolerance.

Loss aversion, the idea that losses psychologically seem larger than comparable gains, is one of the fundamental ideas of prospect theory. There are various ways in which AI tools can interact with loss aversion. In line with Prospect Theory's prediction that people are taking risks in the area of losses in order to prevent them from crystallizing, robo-advisors that automate rebalancing or tax-loss harvesting can assist investors in overcoming their reluctance to realize losses. These AI tools can mitigate the disposition effect, which is partially explained by investors' reluctance to realize losses, by methodically carrying out sales of underperforming assets. The AI can implement a strategy that is logical from the perspective of portfolio management, even if it is emotionally draining for a human investor, because it lacks emotion and does not feel the psychological suffering of a loss.

AI tools have the ability to affect investors' points of reference as well. A robo-advisor might, for instance, compare performance to long-term financial objectives as opposed to cyclical market swings. Because they are less likely to view typical market volatility as substantial losses in comparison to their long-term goals, investors may be able to maintain a more stable risk tolerance as a result of this reframing. However, new reference points may also be unintentionally created by the way AI tools present information. An investor's sensitivity to perceived underperformance may be heightened if an AI tool continuously emphasizes short-term performance or compares their portfolio to a rapidly rising benchmark. This could result in increased risk-taking to "catch up," which is consistent with being in the domain of losses relative to that benchmark.

Another important aspect of AI tools is how they structure information. The way options are presented can have a big impact on decisions, as Prospect Theory shows. AI platforms have the ability to either lessen or increase biases in investment decisions through their user interfaces and communication methods. An AI that explains the uncertain character of returns and the importance of diversification, for example, could promote more sensible risk-taking. On the other hand, an AI that speaks in an overly positive manner or places a lot of emphasis on prior achievements (as some AI trading system marketing may do) may present investing as less risky than it actually is, which could cause overconfidence and excessive risk exposure.

Through the lens of Prospect Theory, sentiment analysis tools can also affect how risk is perceived by measuring market mood. An AI tool may increase an investor's loss aversion and encourage more conservative behavior if it detects a generalized negative sentiment. Strongly positive sentiment, on the other hand, may encourage more aggressive investments by lowering perceived risk. The crucial question is whether these sentiment signals produced by AI result in better-informed choices or simply serve to strengthen preexisting biases like herding, in which investors follow the herd into or out of assets based on perceived gains or losses.

In conclusion, Prospect Theory and Dual Process Theory both offer crucial frameworks for comprehending the complex ways that AI investment tools affect investor risk tolerance and biases in decision-making. In addition to potentially reducing the effects of loss aversion and encouraging more logical, System 2-driven behavior, artificial intelligence (AI) tools also carry the risk of encouraging over-reliance, avoiding critical thinking, or unintentionally producing frames and reference points that generate biased reactions. Leveraging AI's potential for promoting more thoughtful and behaviorally sound investment decisions is a challenge for investors, financial advisors, and technology developers.

6.3 Implications for Practice and Theory

Financial advisors, technology developers, regulators, and the development of behavioral finance theory itself are just a few of the stakeholders who will be significantly impacted by the increasing use of AI tools in the investment landscape. Based on a thorough literature review, the results of this thesis show a complex interaction between AI capabilities and human investor psychology, presenting both opportunities and challenges that should be carefully studied.

Practical Implications for Financial Advisors

An environment where clients have access to or are already using AI investment tools is one in which financial advisors are working more and more. The advisor's role must change as a result. Advisors can use AI to improve their practice and provide more value rather than seeing it as a rival. The potential for AI to support client education and bias mitigation is one important implication. Advisors can help clients recognize their own decision-making patterns and potential biases by using AI-generated insights (from behavioral analytics platforms, for example). For instance, if an AI tool detects that a client is excessively loss averse or frequently participates in herd behavior, the advisor can use this information to guide the client toward more logical investing practices through targeted coaching and conversations. According to research, robo-advisors can reduce biases like the disposition effect (Back et al., 2023). Human advisors can support this by explaining the advantages of these automated techniques, which will strengthen learning.

Additionally, advisors can focus on more complex, value-added services like holistic financial planning, estate planning, and behavioral coaching, all of which call for subtle human judgment and empathy, by using AI tools to relieve them of repetitive tasks like portfolio monitoring and simple rebalancing. In order to serve as a link between sophisticated algorithms and the needs of individual investors, advisors will need to develop their ability to interpret AI-generated recommendations and communicate them to clients in an understandable way. They also play a part in assisting customers in navigating the wide range of AI tools available, pointing them in the direction of trustworthy platforms and away from ones that might be exploitative or badly designed. This suggests that advisors must engage in ongoing professional development to stay up to date on AI developments and how they affect investor behavior and risk tolerance.

Practical Implications for Technology Developers

The primary concern for technology developers is the urgent need to create AI investment tools that are not only highly advanced technically but also morally and behaviorally sound. User interface and interaction design can have a big impact on investor behavior, sometimes in unexpected ways, according to research like that done by Back et al. (2023) on the detrimental effects of some anthropomorphic designs. When creating AI systems, developers should give explainability and transparency top priority. An AI tool should ideally be able to give a concise, understandable justification for any recommendations it makes, such as to sell a specific asset. Instead of encouraging blind automation bias or, on the other hand, skepticism that results in underutilization, this can help engage the investor's System 2 thinking and establish calibrated trust.

Additionally, developers ought to think about adding features made expressly to combat recognized behavioral biases. AI tools might, for instance, offer tailored feedback on prior biassed behaviors, incorporate "cooling-off" periods for rash trading decisions, or present options in a way that encourages investors to make more logical decisions (e.g., emphasizing long-term implications rather than short-term gains/losses). One promising direction is the creation of AI that may adjust its communication style or degree of intervention in response to the identified biases or financial literacy of a particular investor. This needs to be weighed against the possibility of developing systems that are overly authoritarian or that might be interpreted as manipulative. The design and implementation process must prioritize ethical considerations, such as data privacy and the possibility that AI could reinforce existing societal biases if it is trained on biased data.

Practical Implications for Regulators

Regulators face the challenge of fostering innovation in AI financial services while safeguarding investor protection and market integrity. A proactive and flexible regulatory approach is required due to the quick development of AI technologies. The necessity of precise rules for the creation, evaluation, and application of AI investment tools is one important implication, especially with regard to accountability, transparency, and algorithmic bias management. It might be necessary for regulators to set guidelines for how AI tools evaluate and communicate risk as well as how they inform investors of their recommendations. Discussions about algorithmic trading and flash crashes (Kirilenko et al., 2017; Zhang & Zhang, 2024) demonstrate how AI systems have the potential to interact in unexpected ways and increase systemic risk, necessitating continuous monitoring and possibly new supervisory tools.

The moral implications of AI in finance, such as data governance concerns, algorithmic fairness, and the possibility of AI being exploited to take advantage of investor weaknesses, must also be addressed by regulators. It is essential to make sure AI tools don't worsen information asymmetries or produce discriminatory results. Liability for inaccurate AI advice will also need to be clarified as AI assumes more advisory roles. Instead of merely accepting the results of AI tools, regulators can help investors learn how to engage with them critically and effectively through financial literacy programs. Given the global nature of financial markets and the advancement of AI, international cooperation among regulators will also be crucial.

Implications for Theory

The theory of behavioral finance is also significantly impacted by the introduction of AI investment tools. The relationship between human investors and intelligent algorithms may call for the expansion or improvement of current theories, such as Prospect Theory and Dual Process Theory, which offer useful frameworks for understanding AI's impact. A new kind of agency, one that is not human but is capable of complex behaviors and innovatively influencing human choices, is introduced into the decision-making process by AI tools. This puts into question conventional models that mostly concentrate on interactions between people or between people and the market.

Given AI's capacity to systematically reduce some biases (such as the disposition effect through robo-advisors), it is possible that these biases' expression and effects will change in an AI-mediated setting. The emergence of new biases caused by AI or the "half-life" of biases in the presence of AI may give rise to new research questions (e.g., over-reliance on algorithmic outputs, misinterpretation of AI-generated data). It might be necessary for behavioral finance theory to include models of human-AI interaction, taking into account elements that have a significant impact on investor behavior, such as perceived AI intelligence, algorithm trust, and interface design. The concept of "rationality" in investment decision-making may also be reexamined since AI tools provide new standards for ideal conduct, which could move the emphasis from the cognitive limitations of humans to the dynamics of cooperation or conflict between humans and AI. Combining knowledge from behavioral finance, computer science, and complex systems theory, the study of how AI affects market dynamics and collective investor behavior, possibly resulting in new herding or market anomalies, also offers a rich field for theoretical progress.

VII. Conclusion

7.1 Summary of the Research

With an emphasis on understanding its impact on investor behavior, specifically when it comes to risk tolerance and decision-making biases, this thesis set out on a thorough investigation of the increasingly significant role that artificial intelligence (AI) is playing in the field of investing. How do AI investment tools affect investors' risk tolerance and decision-making biases? was the main research question that guided this investigation. The study started out with a number of important goals in order to address this. The main goal was to compile the body of knowledge at the intersection of well-established behavioral finance principles and AI investment technologies (like robo-advisors, algorithmic trading, and sentiment analysis tools). Examining how these AI tools interact with particular cognitive and emotional biases that are common among investors, overconfidence, herd behavior, and status quo bias, and how these interactions are interpreted through the prisms of Prospect Theory and Dual Process Theory were among the secondary goals. The study also focused on finding gaps in the literature that need to be filled and the practical implications of these interactions for different stakeholders.

A thorough Systematic Literature Review (SLR) combined with bibliometric analysis was the methodological approach used for this study. The purpose of this dual approach was to guarantee that the current state of knowledge was captured in both breadth and depth. Using nine customized search queries covering AI investment tools, the chosen behavioral biases, and the fundamental theoretical frameworks, the SLR employed a methodical search approach throughout the Scopus database. Peer-reviewed articles and reviews published between 1994 and 2025, mostly in English, and in subject areas relevant to finance, economics, business, psychology, and decision sciences were the main focus of the specific filters used to ensure the quality and relevance of the extracted academic literature. After a thorough screening of the original corpus of 2,632 records, 90 highly cited papers were selected as the main source of evidence for the qualitative synthesis. Microsoft Excel, which was selected for its transparency and accessibility, was used for data management and preliminary analysis of bibliometric trends (such as publication volumes, geographic distribution of research, and important journal outlets). This methodological rigor made sure that the results were supported by a body of evidence that had been methodically gathered and examined, giving the discussion and conclusions that followed a strong empirical foundation.

The main conclusions of this study, which are covered in detail in the results and discussion chapters, point to a complex and dynamic relationship between investor behavior and AI investment tools. The bibliometric analysis revealed a notable increase in research interest in this field, especially after 2016, which corresponded with the widespread use of AI-powered financial tools and developments in machine learning. With significant contributions from the US, China, the UK, and India, this research is globally distributed and shows how widely applicable AI is in a variety of market contexts. By encouraging disciplined, rule-based investment strategies, AI tools like robo-advisors have the potential to significantly reduce behavioral biases like the disposition effect, according to a thematic analysis of the literature. For example, research by D'Acunto et al. (2019) and Back et al. (2023) showed that robo-advisors could assist investors in making more logical selling decisions, especially in the loss domain. The results did, however, also highlight how complex these relationships are. By discouraging advice-seeking or encouraging automation bias, AI interface design elements like anthropomorphic features can paradoxically lessen the usefulness of these tools (Back et al., 2023; Hildebrand & Bergner, 2021). It was discovered that the effects of algorithmic trading on market dynamics and risk were complex, and that different algorithm types (such as BATs versus HFTs) responded differently to market volatility (Arumugam, 2023). Certain sentiment analysis tools are rapidly gaining popularity, fueled by increasingly complex AI, such as Large Language Models (Fatouros et al., 2023). These tools provide new ways to measure market sentiment, but if not used critically, they may also amplify herd behavior. While AI can be helpful, it is not a cure-all for human psychological tendencies, as the study also confirmed the persistence of overconfidence, herd behavior, and status quo bias in AI-mediated investment contexts. The combination of these results with Dual Process Theory revealed that while AI tools can serve as an external "System 2," supporting analytical decision-making, they also run the risk of reducing investors' own cognitive engagement if they are over-relied upon. Likewise, using Prospect Theory as a framework, it was discovered that AI tools affect investors' reference points and reactions to loss aversion, potentially producing new, negative anchors as well as positive framing. All things considered, the main conclusions show that AI is a strong but complicated force influencing investor behavior, requiring a careful and informed approach to its implementation.

7.2 Contributions to Knowledge

This study adds significantly to the body of knowledge already available at the intersection of investment decision-making, behavioral finance, and artificial intelligence. Both theoretical and practical, these contributions enhance our understanding of well-established frameworks in new settings and provide useful information for a range of financial ecosystem stakeholders.

Theoretical Contributions:

First, this thesis expands on Dual Process Theory's use and understanding in the quickly changing field of AI investment. The research discusses the complex role of AI as a potential modulator of System 1 (intuitive) and System 2 (deliberative) thinking by methodically examining how AI tools like robo-advisors and algorithmic trading systems interact with investors' cognitive processes. According to Back et al. (2023), AI can act as an externalized System 2 that encourages more analytical and less emotionally biased decisions by, for example, automating rebalancing or reducing the disposition effect. However, it also carries the risk of cognitive offloading or automation bias. This draws attention to a crucial conflict: the potential for AI to improve logical decision-making while also potentially reducing investors' own deliberative involvement. In contrast to general applications of Dual Process Theory, this study provides a more detailed understanding by mapping these interactions specifically to AI investment tools. As demonstrated by the different effects of standard versus anthropomorphic robo-advisors, it emphasizes that the influence of AI on cognitive systems is not uniform and is largely dependent on the context of its use and the design of the AI interface (Back et al., 2023; Hildebrand & Bergner, 2021).

Second, the study offers a modern reexamination of Prospect Theory in an investment context mediated by AI. The literature review conducted for the study shows how AI tools can affect important aspects of Prospect Theory, including reference points, loss aversion, and how investment decisions are framed. By reorienting investors' reference points away from short-term market volatility, AI platforms, for example, can strategically frame performance data to align with long-term objectives, potentially stabilizing risk tolerance. On the other hand, some AI tools may unintentionally produce new, potentially harmful, reference points that increase sensitivity to perceived losses due to the continuous flow of data and performance comparisons they enable. The thesis makes a contribution by describing how the algorithmic, emotionless nature of AI can mitigate the behavioral traps associated with loss aversion (e.g., by systematically realizing losses for tax purposes, a task human investors find psychologically difficult). By demonstrating Prospect Theory's applications and possible changes in a highly advanced technological environment where decision are increasingly influenced by algorithms rather than just human reasoning, this investigation enhances Prospect Theory.

Third, in the context of AI investing, this study advances an improved knowledge of behavioral biases, particularly overconfidence, herd behavior, and status quo bias. Although these biases in traditional finance are well-established, research on how they interact with AI tools is still in the early stages. The study summarizes data indicating that artificial intelligence (AI) can have two sides: while robo-advisors may reduce overconfident trading by automating tasks in a disciplined manner, the perceived sophistication of AI may also lead to a new kind of overconfidence in the technology. Similarly, the broad availability of AI-generated sentiment signals or the openness of AI trading strategies may unintentionally encourage new types of algorithmic or AI-influenced herding, even though AI may theoretically decrease herd behavior by encouraging personalized advice. The thesis makes a contribution by carefully defining these relationships, referencing current empirical research, and emphasizing the nuanced, often undetected ways AI impacts the appearance and consequences of these basic human prejudices.

Practical Contributions:

First, the study provides financial advisors with valuable data. It highlights how the role of human advisors is changing in an AI-augmented environment, moving away from routine portfolio management, which AI is becoming better at handling, and toward more sophisticated advisory tasks like behavioral coaching, comprehensive financial planning, and assisting clients in navigating the complexities of AI tools. Advisors can promote more resilient and logical investing practices by using AI-generated behavioral analytics to better understand and address client-specific biases. The study emphasizes how advisors, who serve as an essential human link between technology and client needs, must learn to understand and communicate AI recommendations.

Second, the results have important implications for those who design AI investment tools and develop technology. The study highlights how crucial behaviorally informed design is. Design decisions about transparency, explainability, and the level of anthropomorphism can have a significant impact on user trust, adoption, and ultimately, the AI's ability to mitigate biases, as evidenced by the differing findings of various robo-advisor interfaces (Back et al., 2023). Instead of encouraging passive reliance or producing unexpected behavioral responses, developers are advised to design AI systems that not only maximize financial outcomes but also promote investor understanding and critical engagement (System 2 thinking). The ethical aspects of AI design are also highlighted, especially related to algorithmic bias, data privacy, and the possibility of manipulative nudging.

Third, the study gives policymakers and regulators useful information. Regulatory frameworks need to change as AI becomes increasingly common in the financial markets in order to handle new issues with algorithmic accountability, investor protection, and market stability. The study identifies possible systemic risks that might necessitate new regulatory protections and monitoring systems, such as correlated algorithmic trading or the amplification of market sentiment by AI tools. Moreover, a major regulatory concern is making sure AI tools are fair, transparent, and in line with investors' best interests. The results can help guide the creation of rules for the moral application of AI in finance, encouraging creativity while reducing risks.

Fourth, this thesis provides individual investors with useful insights. The study enables investors to use AI tools more critically and effectively by bringing attention to how these tools can interact with their innate cognitive and emotional biases. Investors can avoid risks like automation bias and over-reliance by realizing that AI is a tool, not a definitive solution, and that its recommendations should be carefully considered. According to the study, investors can make better decisions about which technologies to use and how to incorporate them into their decision-making processes to actually improve their risk management and investment results by continuing to educate themselves on both financial concepts and the operation of AI tools.

Essentially, this study contributes by bridging the gap between the rapidly developing field of artificial intelligence (AI) in finance and the well-established principles of behavioral economics. It does this by providing a nuanced perspective that recognizes both the transformative potential of AI and the persistent complexity of human investor psychology. The study's theoretical expansions and useful insights are intended to promote a better-informed and successful integration of AI into the investment industry.

7.3 Final Remarks and Implications

By the end of this study, it is clear that incorporating AI into investment decision-making is a paradigm shift with significant and far-reaching effects rather than just a small technical improvement. An environment where AI tools are quickly changing how investors view risk, deal with their innate behavioral biases, and eventually navigate the complex dynamics of financial markets has been revealed by the exploration of the body of existing literature. The responses to the central research question, "how these AI tools influence risk tolerance and decision-making biases," are as complex as they are important for the financial industry's future. We are at a point in time where new challenges in cognitive engagement, ethical design, and market stability balance out AI's potential to democratize access to sophisticated investment strategies and reduce human error.

The larger picture of AI and investor behavior is one of cooperation and dynamic interaction. AI is a dynamic field whose capabilities are constantly growing due to advancements in big data analytics, machine learning, and natural language processing. At the same time, investor behavior is adjusting to this new technological environment, even though it is based on timeless psychological principles. This thesis has emphasized that the impact of AI is not deterministic; it does not always increase investors' inclination toward particular biases or their level of rationality. The precise design of the AI tool, the traits of the investor (such as their level of financial literacy and technological trust), and the larger market and regulatory environment are some of the many variables that determine the impact of AI. An effective solution to emotionally motivated, System 1 decisions is a well-designed robo-advisor that encourages long-term, disciplined investing. However, an artificial intelligence tool that floods users with decontextualized data or promotes frequent trading through occult algorithms may worsen overconfidence or promote a gamified approach to investing, both of which could have negative effects.

The study's most important implications include the increased significance of financial and AI literacy. The increasing integration of AI tools into daily financial life necessitates that investors gain a greater understanding of the fundamental principles of finance as well as the capabilities and constraints of the AI systems that they use. Investors run the risk of passively accepting AI-generated advice if they lack the dual literacy necessary to critically evaluate the recommendation or spot possible inconsistencies with their own objectives and risk tolerance. Therefore, educational initiatives must go beyond traditional financial education to include modules on data privacy, algorithmic bias, and human-AI interaction. This is essential for protecting individual investors as well as for creating a market environment where AI tools are applied effectively and productively.

The results also support the idea that, even in the era of AI investment, human interaction is still essential. AI is capable of automating processes, analyzing large datasets, and carrying out plans quickly and accurately, but it is unable to replace the distinctively human abilities of empathy, wise decision-making in complex circumstances, and comprehension of a person's larger emotional landscape and life situation. Instead of being replaced by AI, financial advisors' jobs will shift toward more advanced duties like complex financial planning, behavioral coaching, and assisting clients in integrating AI tools into their lives in a positive and balanced way. Future advisors will probably be skilled at navigating both AI and human psychology, serving as reliable mentors in a financial environment that is becoming more and more complicated.

Looking ahead, there is no doubt that AI in finance will continue to grow. The research gaps this thesis identifies, such as the long-term effects of AI on investor learning, the effects that differ for different investor segments, the systemic implications of interacting AI algorithms, and the changing ethical considerations, all suggest areas that could be explored further. It will take interdisciplinary cooperation to answer these questions, bringing together professionals in the fields of finance, computer science, psychology, ethics, and law. Fostering innovation that advances investor well-being, equity, and financial stability in addition to improving market efficiency and investment performance will be a challenge.

To sum up, this thesis adds to the current discussion by offering a methodical synthesis of the ways in which AI investment tools are currently thought to affect investor risk tolerance and biases in decision-making. It emphasizes that although artificial intelligence (AI) presents previously unthinkable chances to enhance human potential and get around some cognitive constraints, it is not a cure-all. Building behaviorally aware technologies, developing educated and critical users, and establishing strong ethical and regulatory frameworks will all be necessary steps on the road to a future where AI actually empowers investors and improves financial markets. The era of artificial intelligence in investing is essentially about creating a more intelligent, resilient, and human-centered financial ecosystem rather than just developing smarter algorithms. The knowledge gained from this research is intended to be a first step in that direction, promoting ongoing, critical, and productive discussion of the revolutionary potential of artificial intelligence in influencing our investment decisions and, therefore, how we manage our financial lives.

VIII. Limitations of the Study

As explained in the methodology chapter, this study's approach is the main source of its limitations. First off, the results are dependent on the body of published evidence because they are based on a Systematic Literature Review (SLR). Even though the SLR was carried out with much attention to detail, it can only reflect what has been researched and published; any biases or gaps in the original study will inevitably be reflected in this synthesis. Second, the use of a single database (Scopus) limited the bibliometric analysis, even though it provided context. While Scopus is a large database, some relevant publications may have been missed due to the exclusion of other databases like Web of Science or specialized computer science repositories (such as IEEE Xplore or others), which could have somewhat influenced the perception of the research landscape. Due to export constraints, the mini-corpus analysis was limited to the most-cited papers, which may have resulted in the exclusion of more recent, potentially significant research.

Thirdly, primary empirical data collection is not possible due to the desk-based nature of this research. Therefore, rather than being directly observed or tested through new experiments or surveys, the interpretations of behavioral mechanisms are deduced from the findings that others have reported. This restricts the capacity to make firm causal inferences regarding the precise influence of particular AI characteristics on investor psychology across a range of situations. Lastly, as stated in the methodology, time and resource limitations prevented this thesis from undertaking advanced analytical techniques like the machine-learning text mining of the literature corpus, meta-analysis of quantitative studies, or sophisticated bibliometric network mapping (e.g., with VOSviewer). Future research using these techniques may provide more quantitative understanding of the components and development of this area of study.

IX. Recommendations for Future Research

The findings of this thesis and the gaps identified in the literature review chapter, highlight several critical areas for future research. Addressing these questions will be crucial for a more complete understanding of how AI is reshaping investor behavior and for guiding the responsible development and deployment of these technologies.

Long-Term Effects on Investor Learning and Behavior Adaptation

How the extended use of AI investment tools impacts investors in the long run is a major unknown. Does reliance on AI promote learning and internalization of sound investment principles, or does it result in a decline in critical thinking and personal financial decision-making abilities (System 2 engagement)? To determine whether AI tools serve as long-term "teachers" or only as short-term "crutches," longitudinal studies that follow groups of investors as they adopt and use these tools are required. Researchers could look into whether investors make better (or worse) decisions when AI support is removed or when they are presented with new scenarios that the AI is unable to handle.

Differential Impact Across Diverse Investor Populations

Future studies should stop viewing investors as a single entity and investigate how the impact of AI tools differs depending on factors like age, gender, culture, financial literacy, personality traits, and past investing experience. For example, are younger, digitally native investors better able to assess AI outputs critically, or are they more vulnerable to automation bias when using AI? What effects do cultural variations in technological trust have on the adoption and effectiveness of robo-advisors around the world? Large-scale analyses of user data from AI platforms (while respecting privacy) and customized experimental designs may reveal these subtle interactions, opening the door to more individualized and successful AI interventions.

Interaction Dynamics of Multiple AI Systems in Markets

Understanding the resulting behavior from the interaction of multiple, potentially heterogeneous AI systems is crucial as algorithmic trading and AI strategies become more widespread. Research is required to examine the possibility of "AI herding," in which several algorithms respond to comparable signals or data sources, resulting in correlated trading; its effects on market volatility and liquidity; and the possibility of new types of systemic risk. Market simulations and agent-based modeling may prove to be useful instruments for examining these intricate ecosystem dynamics, assisting regulators in anticipating and reducing the risks connected to a market that is becoming increasingly filled with autonomous trading agents.

Ethical Implications and Responsible AI Development

Further research is necessary to fully understand the ethical implications of AI in investment management. This covers the following topics: algorithmic bias (how can developers stop AI tools from reinforcing or exaggerating preexisting societal biases, such as in credit scoring or access to financial advice?), accountability (who is accountable when AI advice results in unfavorable outcomes?), and algorithmic transparency and explainability (how can "black box" AI decisions be made understandable and contestable?). To ensure that these tools actually serve investors' best interests and promote equal market access, more research is required to create strong frameworks and best practices for ethical AI design. Careful ethical consideration and possibly regulatory oversight are also necessary due to the possibility that AI will be used for complex forms of "nudging" or even manipulation.

Measuring and Enhancing Calibrated Trust in AI

According to research, one of the most important factors influencing adoption and adherence to advice is the degree of trust investors have in AI tools (Huang & Chen, 2018; Kumar & Prince, 2023). Future studies should concentrate on developing calibrated trust that is appropriate for the real capabilities and constraints of the AI. This involves understanding the ways in which elements such as AI performance, transparency, user interface design, and the personal traits of investors all play a role in the development of trust. Research could investigate strategies to enhance investors' capacity to evaluate the reliability of AI-generated recommendations, preventing both over-reliance (automation bias) and under-reliance (losing out on advantages).

AI’s Role in Modifying Specific Biases Beyond the Disposition Effect

Although robo-advisors' ability to reduce the disposition effect has been fairly well-documented (Back et al., 2023), further study is required to understand how different AI tools interact with a wider range of cognitive biases, including confirmation bias, overconfidence, anchoring, and status quo bias, in various investment contexts (e.g., active trading vs. long-term investing). The efficiency of various AI interventions (such as gamified learning modules, personalized feedback, and changes to choice architecture) in mitigating these biases could be compared experimentally.

Interdisciplinary cooperation will be necessary to address these research fields, requiring knowledge from the fields of finance, computer science, psychology, ethics, and law. The academic community may develop a better understanding of the changing human-AI relationship in financial decision-making by exploring these paths, which will ultimately create an environment where AI strengthens market integrity and empowers investors.

X. References

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Use of Artificial Intelligence for this study: AI was used for some part of the research, as some specialized academic research tools such as Perplexity, SciSpace, MirrorThink, Consensus and Elicit were tried to search for relevant literature. Some of them proved to be very effective, delivering very specific papers based on the subject of the thesis. AI was also used for brainstorming and structuring the author's thought process. OpenAI's ChatGPT was used to elaborate the Outline, and to narrow every section, subsection as well as their content. Lastly, ChatGPT was also used for random, basic queries such as asking for synonyms or explaining complex, technical terms.