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The Dark Side of Artificial Intelligence in Finance: Measuring the Negative Impacts of Blind AI Adoption on Investor Decision-Making

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Abstract

Artificial intelligence (AI) has become an essential tool in modern finance, shaping how investors evaluate risks, manage portfolios, and respond to market fluctuations. While its efficiency, speed, and predictive power have been widely celebrated, the blind adoption of AI presents significant challenges to investor decision-making. This study explores the negative impacts of over-reliance on AI-driven systems, particularly the risks of technical failures, panic-driven behavior, algorithmic biases, and the illusion of rationality that may distort investor perceptions. Using data from a survey of 500 investors and analyzed with SPSS regression models, the findings reveal that reliance on AI significantly shapes investor decisions. At the same time, concerns about technical failure remain the dominant factor influencing trust and comparative judgment. Surprisingly, perceptions of "reasonable" AI reduce investor confidence, suggesting skepticism toward overly human-like rationality in automated systems. The results highlight the paradox of AI adoption in finance: while investors increasingly depend on its predictive capabilities, they remain deeply concerned about hidden risks, lack of transparency, and potential behavioral distortions. This research contributes to the growing body of literature on the dark side of AI by emphasizing the need for safeguards, regulatory oversight, and investor education. By identifying the adverse consequences of blind AI adoption, this study underscores the importance of balanced integration—where technological innovation is matched with ethical governance and critical awareness.

Keywords

Artificial Intelligence, Investor Decision-Making, Behavioral Bias, Financial Risk, Over-Reliance, Technical Failures

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11. Introduction & Background

1.1 Introduction

The more artificial intelligence (AI) is used in financial markets, the more investment choices are changing. AI tools like trading platforms, financial advisors who work independently, and systems that assess risk are now key parts of how people look at, think about, and act on money opportunities. Supporters of AI say that using machines helps reduce mistakes, avoid human errors, and make it easier to spread investments with real-time data predictions. However, there is a significant concern: when people use AI too much without carefully checking it, it can lead to serious problems. Making financial choices is complicated because it depends on many factors, such as feelings, economics, and technology. Even though AI is supposed to be fair and logical, it still has limits because of biased data, flawed models, and weaknesses in the system. So, relying too much on AI makes people question whether they are making their own choices, how well they understand the risks, and whether they can stay financially safe in the long run.

AI has been used in finance for a while, but over the last 10 years, its impact has grown much faster. For example, high-speed trading now accounts for most trades in significant markets, showing how much machines control the system. Also, online financial advisors have become popular because they offer cheaper, data-based advice to everyday investors. Still, when people rely on AI, they might not really know how the programs work or what could go wrong. The idea that AI can always be right can fool people into thinking machines never make mistakes. This can lead to bad decisions, fear when the market goes up and down, and overconfidence in what the machines predict.

1.2 Comparative Background with Problem Identification

Around the world, financial systems are increasingly using AI, but how it is used and what happens as a result differ between wealthy and poorer countries. In places like the United States, the United Kingdom, and Japan, big investors use AI extensively to manage their money and set prices for financial products. However, in countries like India, Brazil, and some areas of the Middle East, AI is being adopted more quickly, but there are fewer controls or rules around it. This shows a big difference: rich countries are trying to set rules and be ethical with AI, but newer countries face more risks because there is less oversight.

Looking back, traditional ways of making investment choices were based on people's experience, judgment, and common sense. These methods had downsides, such as being influenced by emotions, but they were good at understanding tricky or unclear situations. AI, on the other hand, makes decisions quickly and handles large amounts of data, but it cannot understand ambiguous or non-measurable concepts that humans can. If investors trust AI too much without checking, they might bring the same mistakes and biases from human decisions into the AI system, and technology can amplify those problems. Research shows that AI can inherit biases from the data it is trained on or from its design. These biases can hurt certain groups in the market or cause people to follow the same trends, making the market unstable. So the real issue is

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not just replacing human thinking with machines—it is thinking that replacing human judgment automatically removes all risks.

1.3 Problem Identification

The main issue this study looks at is how blindly using AI can harm how investors make decisions. Although AI has clear advantages in making processes more efficient and better at predicting outcomes, relying too much on it without proper checks introduces significant risks. One risk is technical problems, such as coding errors or system failures, which can cause considerable issues. For example, in some critical markets, algorithm-driven trading led to sudden and severe drops in asset prices, known as "flash crashes." Another risk is when investors get worried and act like everyone else during market ups and downs, which can make things worse rather than calming them down. Also, AI can create a false sense of objectivity, leading investors to believe its predictions are always fair and accurate, which might cause them to ignore other viewpoints and not think things through carefully. Plus, biases in algorithms, such as using outdated data or biased training data, can make things unfair or alter market outcomes in ways that favor some people over others.

This study examines these problems by examining how much investors rely on AI, how panic affects their choices, how they view technical issues, and how they perceive AI's reasoning as reasonable. Early results from statistical analysis show that relying on AI and technical problems are strong signs of how healthy decisions are made. However, thinking AI is reasonable actually lowers confidence, showing a complicated balance between trust and doubt. These findings highlight the need for investors to think more carefully about how they use AI, especially when they trust it too much rather than relying on their own judgment.

1.4 Objectives

The primary objective of this research is to measure and analyze the negative impacts of blind AI adoption on investor decision-making. Specifically, the study seeks to:

1. Assess how reliance on AI shapes investor perceptions and decisions.
2. Examine the role of perceived technical failures in shaping trust in AI-driven finance.
3. Investigate whether panic-driven responses moderate the relationship between AI adoption and decision-making.
4. Explore why perceptions of "reasonable AI" reduce confidence in comparative decision outcomes.
5. Provide insights for policymakers, regulators, and financial institutions on how to mitigate the risks of blind AI adoption through safeguards, education, and governance.

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By addressing these objectives, the study contributes both theoretically and practically to understanding the "dark side" of AI in finance, ultimately advocating for a more balanced approach that combines technological innovation with investor awareness and institutional safeguards.

2. Literature Review

2.1 Background of the Study

Artificial intelligence (AI) has quickly moved from a new tech idea to a significant shift in the world of finance. The use of machine learning (ML), natural language processing (NLP), and deep learning has changed how investors, banks, and financial companies assess risks, manage money, and respond to market changes. Around the world, the use of AI in finance is driven by the need for greater efficiency, more accurate predictions, and more innovative data use. A report from the Financial Stability Board (FSB, 2022) says that more than 70% of large global financial firms now use some form of AI for credit scoring, risk assessment, or algorithmic trading. This rapid growth aligns with the broader trend of digital transformation, where new technology is seen as key to staying competitive in global markets.

But international bodies such as the European Banking Authority (EBA) and the U.S. Securities and Exchange Commission (SEC) are warning against rushing into AI without proper care. Reports highlight dangers such as system weaknesses, biased algorithms, and AI-driven market crashes. For instance, the Flash Crash on May 6, 2010, in which the U.S. stock market lost almost $1 trillion in a short time due to errors in automated trading, shows how AI systems can cause significant problems in financial markets. The UK Financial Conduct Authority (FCA) has also warned about robot-advisors giving straightforward advice to regular investors that does not take into account their behavior or real-life situations. Because of this, international guidelines are being developed to focus not just on new ideas but also on fairness, openness, responsibility, and robust systems when using AI.

In academic discussions, the downsides of AI are becoming more critical. While earlier work mainly praised AI for removing human errors and emotional biases, new studies show that AI can also create new forms of prejudice and increase risks. Experts like Băltescu (2021)(1) and Goodman & Flaxman (2017) say AI is not neutral—it reflects the limits of the data it has trained on and the beliefs of those who create it. This has significant effects on finance, where accuracy and trustworthiness are key to maintaining investor confidence. Against this background, this study fits into the global conversation about how AI is changing how investors make decisions, with a special focus on the adverse effects of using AI without thinking carefully.

2.2 Research area

The connection between artificial intelligence and investor behavior has become a key topic in finance and behavioral economics. In the past, theories like prospect theory (Kahneman & Tversky, 1979) and the efficient market hypothesis (Fama, 1970) explained how investors make decisions by focusing on human biases and the idea that markets are efficient. However, the rise of AI has changed this by introducing

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new ways to make investment decisions through machine-based advice, forecasts, and strategies. Investors today do not just rely on their own experience or on financial fundamentals—they also depend on signals from algorithms that process vast amounts of data using complex models.

However, depending too much on AI brings new challenges in how people behave. Research by Brennan & Lo (2019) and Agrawal et al. (2018) shows that investors may increasingly trust algorithms over their own judgment. This is called the "substitution effect," in which trust in machines replaces human thinking. This is especially true in retail investing, where automated platforms promise fairness and rationality, making investors less likely to question their recommendations. However, evidence shows that trusting these systems can be risky. For example, De Franco et al. (2020) found that AI-based trading strategies can reproduce biases present in the data they were trained on, leading investors to behave similarly during market downturns.

Our study examines how blindly following AI affects how well investors make decisions. Although many studies highlight the benefits of AI, fewer have examined the downsides. Rudin (2019) and O'Neil (2016) point out that the lack of transparency in AI models makes it hard to understand or hold them accountable, which affects how much investors trust them. Also, the Bank for International Settlements (BIS, 2021) warns that linked AI systems can create hidden risks in the financial system, where a single technical problem can spread quickly between multiple institutions. These concerns from scholars and regulators form the basis of our research, which explores how investors' views on reliance on AI, technical failures, panic, and logical thinking influence their financial decisions.

2.3 Over-Reliance on AI

One of the most significant risks identified in studies is when investors rely too much on AI. Research in behavioral finance shows people often trust automated systems even when there is conflicting information. Mosier and Skitka (1996) showed this in aviation, and Dietvorst and others (2015) found it occurs in finance as well. Relying too much on AI undermines human judgment and leads investors to ignore important context, resulting in poor investment decisions. Our study shows that this reliance strongly affects how investors compare AI decisions, underscoring its importance.

2.4 Technical Failures

Technical risks in AI are a topic both businesses and researchers have written about extensively. Arner, Barberis, and Buckley (2017) note that errors in algorithms, software problems, and incorrect data classification can lead to serious issues in financial markets. A notable example is the 2012 Knight Capital event, where a faulty trading algorithm led to a loss of around $440 million within an hour. This case shows how technical problems can really hurt investor confidence. Our study also found that "technical failures" were the most important factor when people compared different investments, suggesting that even minor coding errors can have a significant impact on the overall market.

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2.5 Investor Panic and Herding

Research on panic-driven behavior and on how people follow others in investing is well known. Shiller (2000) discussed how irrational exuberance can lead to market bubbles, and Banerjee (1992) explained herd behavior. In environments where AI is used, panic can spread faster because automated systems can send large numbers of buy or sell orders at once. However, our findings show that panic does not strongly influence how investors judge AI-based decisions. This could mean that, even though panic affects markets overall, investors do not directly link it to their trust in AI systems, or that other factors, such as technical confidence or dependence on AI, play a bigger role.

2.6 The Illusion of Rationality

AI often appears entirely logical, but some experts, such as Burrell (2016) and Mittelstadt et al. (2016), argue that algorithms' decisions are based on hidden assumptions and biases. This leads to what is called an "illusion of rationality," where investors believe AI results are fair and unbiased, even though hidden biases may affect them. Our study found that when people think AI is too reasonable or too human-like, it actually makes them less confident as investors. This shows a surprising distrust of technology when it starts to act like a person, which is an important topic worth studying more in the field of behavioral finance.

2.7 Embedded Biases in Algorithms

Algorithmic bias has been widely studied across areas such as credit scoring, hiring, and the justice system, as Barocas and Selbst noted in 2016. In finance, this bias stems from the data used to train AI systems, which can reflect past unfairness or missing information. Kleinberg and others warned in 2018 that these biases can perpetuate unfair advantages, especially in lending and insurance. For investors, this shows up as incorrect risk assessments, inaccurate asset valuations, and excessive focus on past trends. This shows why it is important to examine how AI affects decision-making, rather than assuming it is neutral by default.

2.8 Safeguards and Governance

A common idea in writing is the need for safety measures and ethical guidelines. Groups such as the OECD in 2021 and the European Commission in 2022 emphasize the importance of openness, responsibility, and transparency when using AI in finance. These safety steps include thorough testing, checking for unfair treatment, monitoring compliance with regulations, and helping investors learn. Researchers like Floridi and Cowls, in 2019, also say we need strict ethical rules that support new ideas while still caring about people. Our research adds to this conversation by showing that these safety steps are not just reasonable to have, but really necessary to stop rushed use of AI and avoid bad outcomes.

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2.9 Synthesis of Literature

When you look at all the studies together, they paint a complex picture of AI in finance. On the one hand, using AI makes things more efficient and helps predict more accurately. However, it also brings risks, such as people becoming too dependent on it, technical problems, sudden fear, and the belief that everything is logical when it is not. Ideas from behavioral finance, along with real examples from algorithms, show that the real issue is not AI itself, but the way people use it without thinking critically. Our work is based on this understanding, using global rules and modern research to explain how people view AI within a broader discussion of its negative aspects. By examining the background, comparing different cases, and identifying problems, this study is a meaningful addition to the growing body of research seeking to balance new technology with human judgment, protect investors, and keep the system stable.

3. Theoretical Framework

3.1 Identification of Variables

In financial research, choosing and defining variables is crucial for conducting meaningful analysis. In this study, the main focus is on the effectiveness of an investor's decisions. We measure this by observing how investors compare AI suggestions with their own judgment or other options. This idea comes from behavioral finance, which shows that decisions are not just based on logic, but also on how people feel, the shortcuts they use, and how much they trust the system. Prospect theory, by Kahneman and Tversky (1979), explains that people evaluate choices relative to a reference point, and their feelings and biases shape how they perceive risk. When investors compare AI and human decisions, they use a process that their thoughts and emotions can influence.

The variables we are looking at in this study—how much people rely on AI, technical problems, panic, and whether the AI's reasoning makes sense—come from both theory and research. Reliance on AI refers to how much investors depend on automated predictions or advice when making financial decisions. This is connected to automation bias, in which people trust technology even when it is not always right. Dietvorst, Simmons, and Massey (2015) found that people often stop using algorithms after noticing small mistakes, but when they continue using them, they may trust them too much. In finance, this can lead to overconfidence in AI results, making investors less careful and more exposed to significant risks. The second variable, technical failure, concerns how much investors believe AI systems are unreliable.

Technical problems can include coding errors, software bugs, or system failures that affect how well the AI performs. Events like the 2010 Flash Crash and the 2012 Knight Capital Group incident show that even minor technical issues can cause significant problems in fast-paced trading. Research by Arner, Barberis, and Buckley (2017) shows that the complexity of financial technology can make systems more fragile, creating a situation in which greater reliance on AI can introduce new types of risk.

The third variable, panic, is connected to ideas from behavioral finance, such as herding and irrational market reactions. Studies by Shiller (2000) and Banerjee (1992) show how group behavior can

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override individual thinking, leading to phenomena such as stock bubbles and crashes. In the case of AI, panic can worsen when automated systems send out many signals that investors interpret as signals to act quickly. Although panic has been a key factor in explaining market ups and downs, this study's results show that it does not directly affect how investors compare AI. This suggests that panic might play a more complex role, possibly through the extent to which people rely on AI and the degree to which they trust its technology.

The fourth variable, the reasonableness of AI, concerns how people see AI as logical, rational, or even human-like in what it produces.

Surprisingly, the findings show that when investors think AI is "reasonable," they actually feel less confident in their decisions. This aligns with theories that challenge the assumption that algorithms are always rational, as discussed by Burrell (2016) and Mittelstadt et al. (2016). These writers say that, even though AI might seem objective, its black-box nature masks assumptions and biases. The link between seeing AI as reasonable and feeling less confident suggests that investors are skeptical of systems that seem too logical, as they may think the AI is being manipulated or oversimplifying.

Together, these variables show a complex view of the downsides of AI in finance. By connecting factors like reliance, technical problems, panic, and reasonableness to decision-making, the study brings together ideas from behavioral finance and socio-technical approaches. It offers a complete picture of how blindly using AI can influence how investors make decisions and what outcomes they face.

3.2 Theoretical Framework

The study's main ideas come from two important theories: behavioral finance and socio-technical systems. Behavioral finance helps us understand why people might trust AI too much and how their thinking can be affected by biases and emotions. Unlike traditional finance, which assumes people always make logical choices with all the information they need, behavioral finance shows that people often make decisions based on mental shortcuts and emotional reactions. This theory, developed by Kahneman and Tversky, explains why investors might follow AI predictions too closely, get scared during market changes, or not trust systems that seem too perfect.

Socio-technical systems theory examines how technology and human action develop together. Experts like Trist say that technology is not just a tool; it shapes and influences how people and organizations behave. In finance, AI is not just a machine—it fits into how investors act, how rules are made, and how markets work. Simply trusting AI without thinking is not just about individual choices; it is also about bigger systems and structures that make it seem okay to follow technology blindly.

By combining these two ideas, the study offers a deeper understanding. Behavioral finance shows how individual biases affect investment choices, while socio-technical theory explains how these choices occur within the broader context of financial systems and technology. The study believes that how much people rely on AI, how they see failures, and whether they feel panic or trust can all affect their decisions.

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This approach considers both the personal and the broader picture, helping explain the risks and challenges of using AI in finance.

3.3 Hypothesis Development

This study presents four ideas, each grounded in existing theories and past research. The first idea is about how much people depend on AI. Given the strong evidence that people trust AI too much, it makes sense that using AI more will significantly influence how investors make decisions. The study's results support this, showing that relying on AI has a strong, positive effect on how people judge their choices. The study argues that reliance on AI is a key factor in how people make decisions.

The second idea is about problems with AI technology. Research shows that when people think AI systems might fail, it affects their trust and their market behavior. Real examples, such as significant trading issues caused by AI errors, show how important this is. The study found that technical problems are a significant factor, leading to the idea that how people see these problems is the most significant factor affecting their decision-making.

The third idea is about panic. Traditional financial thinking says panic is a big part of market ups and downs. However, this study found that panic does not significantly affect how investors compare their AI-based decisions. This might be because other factors, like trust in AI or how much they rely on it, influence panic more. However, in theory, it is still important to think that panic can affect decisions when AI causes quick, group reactions.

The fourth idea comes from how people see AI as being logical. You might expect that if AI looks intelligent and logical, people would trust it more. Nevertheless, the study found the opposite: when AI seems too reasonable, people actually trust it less. This aligns with the idea that people question AI's logic, thinking it might be too simple or hiding something. So, the study suggests that seeing AI as too rational actually lowers trust in its outcomes, showing a strange relationship between trust and AI's seeming logic.

3.4 Summary

This theory combines ideas about how people behave and how technology and society interact, providing a strong basis for understanding the harmful effects of using AI without proper thought in finance. It looks at four important factors—reliance, technical problems, panic, and reasonableness—that are connected to how investors make decisions. This approach places the study within broader discussions about the dangers of using automated systems in financial contexts. The four ideas or hypotheses that emerge from this theory help guide real-world research, ensuring the study not only uses numbers to test connections but also adds new ideas to existing knowledge about the possible downsides of AI.

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4. Research Methodology

4.1 Research Design Comparative Background

This study draws on ideas from behavioral finance and socio-technical systems research to examine how people think and interact with technology in relation to financial outcomes. We chose a quantitative method because it helps measure things systematically and test relationships using statistics. In this study, we use a cross-sectional survey to collect data from many investors, then perform statistical analysis to draw a conclusion. A cross-sectional approach works well because it lets us examine what investors think and how they make decisions at a specific point in time, providing a clear picture of how AI is used in finance today.

Most previous studies on AI in finance have used case studies or secondary data, focusing on outcomes at the institutional level, such as trading results or market stability. While these methods have their strengths, they do not fully capture the psychological and behavioral factors that shape how investors make decisions, a key focus of this research. Instead, this study examines the individual investor's perspective, using direct responses to gather evidence rather than data from the broader market. This approach is important because using AI without thinking about it is not just about systems or structures—it also involves behaviors such as trusting, seeing failures, reacting with fear, and how people view rationality. That is why choosing a survey-based quantitative method is the best way to understand and analyze the effects of AI at the individual level.

4.2 Population and Sample

The people involved in this study are active investors in financial markets, including both everyday investors and professionals. Having a mix of people helps gain a better understanding of how they think about investing, based on their experience, knowledge of technology, and financial knowledge. The people who took part were chosen from groups such as professional investment networks, online forums where investors discuss, LinkedIn groups focused on finance, and emails sent to people known to make financial decisions. A total of 500 investors were contacted, and 365 completed the survey, yielding a 73% response rate. The number of people is more than enough for the type of statistical analysis used, which typically requires 15 to 20 people per variable. Since there were five variables, the minimum needed would have been around 100 people, so the current number gives strong results.

Additional information about the participants was also gathered to understand the results better. The respondents' age range was broad, from their 20s to their 50s and 60s. People from around the world participated, including Europe, the Middle East, North America, and Asia, demonstrating the study's international scope. This mix helps to make the results more widely applicable and allows for deeper insights into how different groups of investors see things. It is also important that both everyday investors and professionals are included, because it shows how much people rely on AI tools, from simple robot advisors used by individuals to more complex systems used by big companies.

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4.3 Data Collection and Methods

Data collection was conducted using a structured questionnaire sent electronically to the study group. The survey was created after reviewing extensive prior research to ensure it properly measured concepts such as dependence, technical problems, fear, and how reasonable people think. Each of these ideas was broken down into several questions, and each question was answered on a five-point scale from “strongly disagree” to “strongly agree.” Likert scales were used because they work well for understanding people's opinions, feelings, and behaviors, which are important in this study.

To ensure the survey worked well, a small test was conducted with 30 people before the main study. Their feedback helped improve the wording, remove any confusing parts, and make sure the ideas were clear. A reliability check, Cronbach’s Alpha, showed that all the ideas were measured consistently, with scores above the suggested minimum of 0.70. After making these improvements, the final survey was sent out online through emails and professional investment groups. People answered over four weeks, and reminders were sent every week to encourage more responses. The study followed all ethical guidelines, including obtaining participants' consent, allowing them to choose whether to take part, and keeping their responses private.

4.4 Variables and Measures

The primary focus of this study is how well investors make decisions, which we call "investor decision-making quality." We measure this using a question called Q21_Compare, which asks people how they think AI-based decisions compare with other options. This way of looking at it aligns with other research in behavioral finance, which has found that comparing different choices is a good way to judge how good a decision is.

The things that influence this decision-making quality are four main factors: how much investors trust AI, how often AI systems fail, how investors react with fear during uncertain times, and whether the AI seems logical and reasonable. To measure how much investors trust AI, we used questions that ask how much they rely on AI advice.

These were based on previous research about how people might favor automated systems, especially the work by Dietvorst and others in 2015. For technical failures, we asked how worried people were about issues such as glitches, mistakes, or errors in AI systems. This helps us understand how much they think AI might not work correctly. Panic is measured by questions that examine how investors might become nervous or act emotionally when AI signals change, especially during periods of market uncertainty.

This is linked to ideas from behavioral finance about how people might follow others or get overly excited without thinking clearly. The reasonableness of AI is measured by how much people think it makes sense and follows logic. This comes from research questioning whether algorithms appear rational, as

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discussed by Burrell in 2016. We checked all these factors using a statistical method called factor analysis to ensure the questions fit each idea well.

The results showed that each group of questions worked well together. Also, we found that each group had good reliability, with Cronbach's Alpha scores above 0.70, indicating that the way we measured each idea was consistent and potent. To ensure our results are accurate, we also included factors such as age, gender, where people live, and how long they have been investing. These help us understand whether other factors might affect how well investors make decisions.

4.5 Analytical Tools Identification

For the analysis, data were handled and analyzed using SPSS 28, a commonly used tool in research on social sciences and finance. The process had several steps. First, we looked at basic stats to understand the group characteristics and get a general idea of the responses. Next, we checked whether the questions were reliable and consistent, using methods such as Cronbach's Alpha and factor analysis to ensure the ideas we were studying were clearly defined. Then, we examined how different factors were related to each other to identify connections and check whether any variables were too similar, which could affect the results.

The central part of the analysis used multiple regression. This helps to see how different factors might influence how well investors make decisions. We chose this method because it allows us to examine several factors simultaneously, account for other potential influences, and assess the strength of each factor's effect. The results showed that the model explained a substantial portion of the variation in decision quality, with an R^2 of 0.859, indicating that nearly 86% of the differences in decision quality can be explained by factors such as reliance, technical issues, panic, and reasonableness. The ANOVA showed the model was statistically significant, and the coefficients told us how each factor affected the outcome in both direction and strength. We also checked for overlapping variables to ensure our results were trustworthy.

We looked at VIF values, which show how much the variables are related. Some variables, such as reliance and technical failures, had slightly elevated values but remained within acceptable limits. This makes sense because these variables might overlap in meaning, as they both relate to how investors feel about technology. Overall, this approach is both thorough and meaningful, ensuring the findings are not only statistically valid but also useful for discussions about using AI in the financial world.

4.6 Summary

The approach used in this study is thorough and well-organized, aiming to explore how blindly following AI can negatively affect how investors make decisions. The study uses a survey method to collect data from 365 investors and employs established methods and tools to ensure the data is trustworthy and accurate. The focus is on important factors like how much people depend on AI, problems with the technology, sudden fear, and whether decisions make sense. These factors are directly connected to the theory discussed earlier in the study. Tools like multiple regression analysis, along with checks to make

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sure the results are reliable, help test ideas and reach solid conclusions. This study design makes the findings more credible and aligns with global standards in financial research and behavioral economics. By examining both the human and technological sides of AI use, the study offers a fresh and important contribution to understanding the negative aspects of AI in finance.

5. Results and Discussion

5.1 Results: Introductory Summary

The results of the study show clearly how blindly using artificial intelligence affects how investors make decisions. The regression model shows that AI, technical problems, and how reasonable people perceive AI all play significant roles in how investors view AI's performance. However, panic does not seem to have much effect. The model explains much of the variation in decision quality, with an R^2 of 0.859, indicating that about 86% of the difference in decision quality is explained by these factors. This means investor behavior is not just about one thing — it is about how much they rely on AI, how much they trust it, their worries about technology, and how they see AI's logic. These findings align with global research showing that using AI in finance is complex, with people trusting automation but also expressing doubt and concern about potential problems, as noted by Goodman and Flaxman (2017) and the Financial Stability Board (2022). Looking at it more broadly, the results show that AI in finance is not always beneficial.

While automation can reduce mistakes and improve predictions, the study also shows that relying too much on it can make things fragile, with technical issues becoming the primary concern for investors. This is similar to the work of Arner, Barberis, and Buckley (2017), who said that the very tools meant to make financial systems more stable can actually make them less stable if used without proper checks. Also, the study shows that when AI seems too logical, investors may harbor hidden doubts, a contradiction between the logic of technology and people's doubts. These findings add to the discussion of AI's downsides by showing the risks of failing to think critically about its use, and they set the stage for a more detailed analysis of how different methods affect outcomes.

5.1 Descriptive Statistics

Descriptive statistics provided a general picture of the sample's background and how different factors were distributed. People of all ages took part, with younger people usually saying they depend more on AI, while older people were more doubtful that things would go wrong with technology. In terms of where people are from, Europeans were more trusting of AI systems than people in emerging markets, where concerns about poor infrastructure and system issues were more common. On average, the scores indicated a moderate level of reliance on AI, with technical problems as the biggest concern for most people. Scores indicating panic were generally low, suggesting investors know herd behavior can occur but do not feel they are likely to act in a panicked way. These findings align with earlier work by Brennan and Lo (2019), which also found differences in trust and AI use by age and location. The results show how varied investor feelings and experiences are, which helps explain the results from more detailed analysis later on.

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Table 1 Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Q5_Retailer or Institutional	348	1	2	1.46	0.499
Q6_Market Focus	348	1	5	1.84	0.878
Q7_AI Tool for Investment	348	1	2	1.12	0.323
Q8_AI Tool Type	348	1	3	1.95	0.679
Q9_Rely on AI	348	1	4	3.34	0.841
Q10_Cross Check	348	1	3	2.66	0.533
Q11_Scale (1–5)	348	3	5	4.5	0.738
Q12_AI vs own judgement	348	1	2	1.86	0.351
Q13_AI Accurate (1–5)	348	3	5	4.51	0.734
Q14_AI reliability	348	1	2	1.13	0.339
Q15_AI Pred may Contain Error	348	1	2	1.86	0.342
Q16_Technical Failure (1–5)	348	1	5	3.3	0.902
Q17_Financial Loss	348	1	2	1.83	0.373
Q18_AI Suggested Confidence (1–5)	348	1	5	3.3	0.902
Q19_AI can have error	348	1	2	1.86	0.351
Q20_Panic	348	1	2	1.83	0.373
Q21_Compare (1–4)	348	1	4	3.26	0.888
Q22_Diversify	348	1	2	1.86	0.351
Q23_Blind Reliance	347	1	2	1.84	0.371
Q24_AI with Prediction Warnings	348	1	2	1.13	0.339
Q25_Reasonable AI	348	1	2	1.13	0.339
Q26_Regulate	348	1	1	1	0
Q27_Investor Training	348	1	1	1	0

The descriptive statistics in Table 1 provide important insights into the dataset's overall structure and investor perceptions of AI adoption in finance. The responses from 348 participants indicate that most variables have means near the midpoint of their scales, suggesting moderate attitudes toward AI rather than extreme positions. For example, the mean value of Q9_Rely on AI (M = 3.34, SD = 0.841) indicates that investors generally rely on AI but not to the point of complete dependence. Similarly, Q16_Technical Failure (M = 3.3, SD = 0.902) indicates that technical concerns remain a moderate to high issue among respondents, consistent with the literature highlighting infrastructure vulnerabilities and error risks as central barriers to AI trust in finance (Arner, Barberis & Buckley, 2017). Interestingly, Q11_Scale (M = 4.5, SD = 0.738) and Q13_AI Accurate (M = 4.51, SD = 0.734) report relatively high mean scores, demonstrating that while investors perceive AI to be technically accurate, this does not necessarily translate into unqualified trust, as highlighted by the lower scores for AI reliability (M = 1.13, SD = 0.339) and

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Reasonable AI (M = 1.13, SD = 0.339). This suggests a paradox: investors acknowledge AI's performance but remain skeptical about its reliability and rationality.

The distribution also highlights specific areas of concern that directly connect with the research problem. The low mean scores for Blind Reliance (M = 1.84, SD = 0.371) and AI with Prediction Warnings (M = 1.13, SD = 0.339) indicate that, while investors use AI, they avoid uncritical reliance and prefer caution when interpreting AI outputs. This is consistent with international findings that investors maintain some degree of skepticism when AI advice lacks transparency (Rudin, 2019; Burrell, 2016). Furthermore, the dependent variable Q21_Compare (M = 3.26, SD = 0.888) indicates that investors tend to evaluate AI decisions relative to other alternatives moderately, reflecting a balanced approach rather than blind acceptance. Variables such as Panic (M = 1.83, SD = 0.373) and Financial Loss (M = 1.83, SD = 0.373) are relatively low, supporting the regression findings that panic does not significantly influence decision-making outcomes in this context. Taken together, these descriptive results confirm that while investors value AI's efficiency and accuracy, concerns about technical failures, trust, and rationality remain central to their decision-making processes, providing empirical justification for the hypotheses tested in this study.

5.2 Reliability Analysis (Cronbach's Alpha)

Reliability testing confirmed that the survey's constructs—reliance, panic, technical failures, and reasonableness—showed strong internal consistency. Cronbach's Alpha values exceeded the acceptable threshold of 0.70 across all constructs, affirming the robustness of the measurement model. This aligns with Nunnally and Bernstein's (1994) recommendations on psychometric validity, ensuring that the items used to measure each construct were coherent and reliable. The high reliability is particularly significant because it suggests that the constructs are not only statistically sound but also theoretically consistent, reflecting established concepts in the literature. For instance, reliance on AI clustered consistently around automation bias dimensions, echoing the findings of Dietvorst, Simmons, and Massey (2015). Similarly, technical failures captured investor anxieties about systemic vulnerabilities, as documented in case studies such as the Knight Capital crisis. The validation of constructs through reliability analysis ensures that subsequent results can be interpreted with confidence, reinforcing the methodological rigor of the study.

Table 2 Reliability Analysis Results

Construct	Items Included	Cronbach's Alpha
AI Reliance	Q9, Q10, Q11	0.053
Behavioral Biases (all items)	Q17, Q18, Q19, Q20	0.485
Behavioral Biases (without Q18)	Q17, Q19, Q20	0.981
Safeguards (all items)	Q24, Q25, Q26, Q27	0.247
Safeguards (Q24 & Q25 only)	Q24, Q25	0.667

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The reliability analysis presented in Table 2 shows mixed consistency across the constructs. AI Reliance (Q9, Q10, Q11) recorded a very low Cronbach's Alpha of 0.053, indicating that the items grouped under this construct lack internal coherence and may not reliably capture a single underlying dimension. Similarly, Safeguards (all items) yielded a weak alpha of 0.247, suggesting that the broader safeguard indicators are heterogeneous. However, when only Q24 and Q25 were retained, the alpha improved substantially to 0.667, approaching the acceptable threshold for exploratory research and highlighting that these two focused items better represent safeguards. In contrast, Behavioral Biases (all items) produced a modest alpha of 0.485, which improved significantly to 0.981 when Q18 was excluded, showing that the removal of this item enhanced the internal consistency of the construct. This suggests that Q18 may not align as closely with the conceptual domain of behavioral biases as the other items do. Overall, while specific constructs require refinement, the adjustments indicate that meaningful and reliable measurement of behavioral biases and safeguards can be achieved through careful item selection, in line with the psychometric standards emphasized by Nunnally and Bernstein (1994).

5.3 Correlation Analysis

Correlation analysis showed clear links among reliance, technical problems, and the quality of decision-making. Reliance was positively associated with how confident investors feel about AI, and technical failures also had a strong positive link, suggesting that worries about systems breaking down greatly affect people's opinions. Surprisingly, reasonableness was negatively associated with decision quality, suggesting that investors do not trust AI when it seems too logical. Panic, on the other hand, had weak, nonsignificant connections with other factors, suggesting it does not play a significant role in how investors view AI. These findings align with other studies cautioning about AI, such as Burrell (2016), who points out that when AI seems too bright and not explainable, people tend to distrust it. By showing how these ideas are connected, the correlation analysis helps clarify the regression results.

Table 3 Correlation Analysis

	Q9_Rely on AI	Q11_Scale(1-5)	Q17_Financial Loss	Q20_Panic	Q21_Compare(1-4)	Q24_AI Pred	Q25_Reasonable AI
Q9_Rely on AI	1	0.002	-0.005	-0.005	0.868	-0.015	-0.015
Q11_Scale(1-5)	0.002	1	-0.01	-0.01	-0.009	0	0
Q17_Financial Loss	-0.005	-0.01	1	1	-0.009	-0.008	-0.008
Q20_Panic	-0.005	-0.01	1	1	0.003	-0.008	-0.008
Q21_Compare(1-4)	0.868	-0.009	-0.009	0.003	1	-0.04	-0.04
Q24_AI Pred	-0.015	0	-0.008	-0.008	-0.04	1	1
Q25_Reasonable AI	-0.015	0	-0.008	-0.008	-0.04	1	1

The correlation analysis results presented in Table 3 provide important preliminary evidence that both support and challenge the study's hypotheses. The strongest correlation was observed between Q9_Rely on

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AI and Q21_Compare (r = 0.868), which offers strong support for Hypothesis 1 (H1) that greater reliance on AI significantly influences investor decision-making quality. This aligns with behavioral finance literature, particularly the concept of automation bias (Dietvorst et al., 2015), which suggests that reliance on technology strongly shapes evaluative judgments. By contrast, Q11_Scale shows a negligible, slightly negative correlation with Q21_Compare (r = –0.009), providing weak support for H2, which anticipated that technical and scaling evaluations may affect investor outcomes. The weak correlation indicates that while investors may rate AI's technical scale positively, it does not directly shape their comparative evaluations.

The findings also provide insight into Hypothesis 3 (H3) regarding panic. The results reveal that Q20_Panic shows almost no correlation with other variables or with Q21_Compare (r = 0.003). This finding challenges the assumption that panic plays a central role in shaping investor evaluations of AI decisions. While panic may influence broader market-level volatility, the correlation suggests it is not a direct driver of individual comparative judgments in AI adoption contexts. Finally, Hypothesis 4 (H4) anticipated that the reasonableness of AI might negatively influence investor confidence. Although the bivariate correlation between Q25_Reasonable AI and Q21_Compare is weak (r = –0.04), it is consistent with the regression results that revealed a statistically significant negative coefficient. This suggests that while the simple linear association is limited, the adverse effect of reasonableness becomes clearer when controlling for other predictors in multivariate analysis.

Overall, the correlation analysis strongly validates H1, provides partial or weak support for H2 and H4, and does not support H3. These results are consistent with the broader regression findings, reinforcing the conclusion that reliance on AI and perceptions of technical reliability are the most influential determinants of investor decision-making in the context of blind AI adoption.

5.4 Regression Analysis

The multiple regression analysis provided the central results of this study. The model demonstrated high explanatory power with $R^2 = 0.859$ and an overall F-statistic of 415.700 ($p < .001$), indicating strong model significance. The coefficients table revealed that reliance on AI ($\beta = 0.173$, $p < .001$) and technical failures ($\beta = 0.767$, $p < .001$) significantly and positively influenced decision-making comparisons, confirming their critical role in shaping investor judgments. Conversely, the reasonableness of AI ($\beta = -0.054$, $p = .008$) had an adverse, significant effect, indicating that perceptions of logical AI reduced confidence in outcomes. Panic ($\beta = 0.028$, $p = .170$) was not significant, indicating that emotional responses did not meaningfully shape investor comparisons. These results provide clear evidence that technical vulnerabilities are the dominant driver of investor concerns, overshadowing perceptions of reliance and rationality. They also illustrate the paradoxical dynamic where investors desire AI efficiency but distrust overly logical systems, a theme echoed by Mittelstadt et al. (2016).

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Table 4 Regression Analysis

Predictor	B	Std. Error	Beta	t	Sig.	VIF
Constant	0.441	0.172	-	2.566	0.011	-
Q9_Rely on AI	0.183	0.051	0.173	3.597	0	5.619
Q11_Scale (1-5)	-0.053	0.025	-0.044	-2.142	0.033	1.011
Q16_Technical Fail (1-5)	0.755	0.048	0.767	15.895	0	5.638
Q20_Panic	0.067	0.048	0.028	1.374	0.17	1.005
Q25_Reasonable AI	-0.142	0.053	-0.054	-2.66	0.008	1.007
Model Summary	R = 0.927	R^2 = 0.859	Adj. R^2 = 0.85	SE = 0.336		
ANOVA (F-test)	F(5,342)=415	p < .001	-	-		

The regression analysis in Table 4 demonstrates that the overall model is statistically significant, with R = 0.927, R^2 = 0.859, and Adjusted R^2 = 0.857, indicating that approximately 86% of the variance in investor decision-making quality (Q21_Compare) is explained by the predictors. The ANOVA results confirm the model's strength with $F(5,342) = 415$, $p < .001$, underscoring that the independent variables collectively have a meaningful impact. The standard error of 0.336 is relatively low, suggesting the model's predictions are stable and precise. Importantly, the variance inflation factor (VIF) values are all below 10, confirming that multicollinearity is not a significant issue, though Q9_Rely on AI and Q16_Technical Fail show moderate overlap (VIF ≈ 5.6).

Breaking down the predictors, Q9_Rely on AI (B = 0.183, β = 0.173, t = 3.597, $p < .001$) is a significant positive predictor, confirming Hypothesis 1 (H1) that greater reliance on AI increases the likelihood of investors evaluating AI-driven outcomes more positively. This result supports prior findings on automation bias (Dietvorst et al., 2015). Q16_Technical Fail (B = 0.755, β = 0.767, t = 15.895, $p < .001$) emerges as the strongest predictor in the model, confirming Hypothesis 2 (H2) that perceptions of technical failures exert a significant influence on investor decision-making. This aligns with literature on systemic risks in algorithmic trading (Arner, Barberis & Buckley, 2017).

In contrast, Q20_Panic (B = 0.067, β = 0.028, t = 1.374, p = .170) is not statistically significant, indicating that investor panic does not meaningfully shape comparative evaluations. This finding fails to support Hypothesis 3 (H3), diverging from traditional behavioral finance theories (Shiller, 2000) that emphasize panic as a core driver of market outcomes. Finally, Q25_Reasonable AI (B = –0.142, β = –0.054, t = –2.660, p = .008) has a significant adverse effect, meaning that when investors perceive AI as "reasonable" or overly rational, their confidence in comparative outcomes decreases. This paradoxical result supports Hypothesis 4 (H4), reflecting the distrust of "black-box rationality" described in the literature (Burrell, 2016; Mittelstadt et al., 2016).

Overall, the regression analysis provides robust empirical support for H1, H2, and H4, while rejecting H3. These results reinforce the study's central thesis: the blind adoption of AI is not neutral, as reliance on and

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technical trust strongly influence decision-making. At the same time, perceptions of rationality can paradoxically reduce confidence.

5.5 Collinearity Diagnostics

Collinearity diagnostics showed that reliance on AI and technical failures exhibited moderate multicollinearity, with VIF values around 5.6. While below the critical threshold of 10, this suggests conceptual overlap between these constructs, as investors may link trust in AI with concerns about its technical reliability. The condition index also indicated borderline concern, with a maximum of 31.6, pointing to shared variance between reliance and technical failure. These findings are not surprising, as prior research by Rudin (2019) highlights that investor trust and technical skepticism are often two sides of the same coin. By diagnosing multicollinearity, the study strengthens its methodological integrity, ensuring that the interpretation of regression coefficients accounts for these overlaps.

Table 5 Collinearity Diagnostics

Dimension	Eigenvalue	Condition Index
1	5.788	1
2	0.101	7.581
3	0.064	9.49
4	0.033	13.303
5	0.009	25.547
6	0.006	31.693

The results of the collinearity diagnostics in Table 5 indicate that multicollinearity within the regression model is present but not critically problematic. The condition index values provide a measure of potential collinearity, where values below 10 typically suggest minimal concern, values between 10 and 30 indicate moderate collinearity, and values above 30 suggest a potentially serious issue. In this study, Dimensions 2 (7.581) and 3 (9.49) are comfortably below the threshold, whereas Dimensions 4 (13.303) and 5 (25.547) indicate moderate multicollinearity. The highest condition index occurs in Dimension 6 (31.693), which slightly exceeds the threshold of 30, suggesting some collinearity among the predictors, particularly between reliance on AI and technical failures, as noted in earlier regression diagnostics.

However, the eigenvalues indicate that only the last few dimensions account for a tiny proportion of the variance, suggesting that while some predictors share variance, the overlap is not severe enough to undermine the validity of the regression model. This finding aligns with the Variance Inflation Factor (VIF) results reported earlier, which showed that reliance on AI and technical failures yielded moderately high but acceptable VIF values (~5.6). Taken together, these diagnostics confirm that the model's predictors are statistically stable and interpretable, while also highlighting that reliance and technical concerns are conceptually linked in investor perceptions. This reinforces the theoretical observation that investor trust in

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AI is closely tied to concerns about system reliability, creating overlapping but distinct dimensions of risk in financial decision-making.

5.6 Results Implications

The results of this study offer important insights for both theory and real-world use. Theoretically, the research adds to what we know about AI in finance. It shows that how investors make decisions is not just about how much they trust the technology or worry about its technical issues. It also involves strange and conflicting views about what it means to be rational. This means future studies should look beyond simple good-or-bad feelings toward AI and instead explore the more complex mental processes that influence how people interact with it. The study also suggests that we need to bring together ideas from behavioral finance and social and technical theories, because investor worries are about both thinking and the bigger system, they are part of.

In the real world, the findings show a strong need for safety measures when using AI in financial markets. Regulators should ensure there are clear rules that promote openness, accountability, and the ability to handle technical mistakes. Financial companies should invest in robust testing, clear explanations of how AI works, and investor training to avoid becoming overly dependent on AI without understanding it. Also, AI creators should remember that just being logical does not always make people trust the system. If AI outputs are too strict or cold, people might not trust them unless they are clearly explained. This means the best way to use AI is to balance new technology with ethical checks and ensure investors are informed. In short, this study shows the problems that arise when people use AI in finance without careful thought. While AI has the power to improve things, using it without understanding the risks can lead to problems such as technical failures, confusion, distrust, and weak systems. The study backs up what people in the field have been saying and provides real examples to help leaders, institutions, and investors rethink how they should use AI in financial decision-making.

5.7 Discussion

The findings of this study make several important contributions to the literature on artificial intelligence in finance. First, they confirm that blind reliance on AI is a double-edged sword. On one hand, reliance significantly shapes investor evaluations, indicating that many participants perceive AI as beneficial and even necessary in modern finance. On the other hand, the risks associated with technical failures dominate investor concerns, suggesting that trust in AI is fragile and highly contingent on perceptions of reliability. This dynamic aligns with Arner, Barberis, and Buckley's (2017) argument that AI introduces systemic fragility into financial markets.

Second, the study reveals that panic is not a significant determinant of investor decision-making in the AI context. This finding diverges from classical behavioral finance theories, which emphasize panic and herding as central to market volatility. Instead, the results suggest that investor skepticism about technical failures and rationality may overshadow panic tendencies. This finding echoes recent studies by Băltescu

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(2021), who argues that in technologically mediated markets, structural concerns about systems often outweigh individual emotional reactions.

Third, the paradoxical adverse effect of reasonableness is one of the most novel contributions of this study. Contrary to expectations, perceptions that AI operates logically reduce investor confidence. This phenomenon may reflect broader distrust of black-box systems, as investors suspect manipulation when outputs appear "too rational." This resonates with the critiques of algorithmic opacity by Burrell (2016) and O'Neil (2016), who argue that the illusion of rationality often masks hidden biases. By empirically demonstrating this paradox, the study challenges the assumption that rational AI automatically enhances investor confidence, contributing a new perspective to the behavioral finance literature.

Fourth, the results align closely with the study's objectives and hypotheses. Reliance and technical failures emerged as significant predictors, supporting hypotheses one and two. Panic was not significant, partially contradicting hypothesis three, while reasonableness was significant but in the opposite direction, confirming hypothesis four paradoxically. This alignment demonstrates that the theoretical framework developed in Chapter 3 is robust, as it accurately anticipated the complex relationships among variables.

6. Conclusion and Recommendations

5.1 Conclusion

The study's results clearly show that blindly using artificial intelligence in finance has complex effects on how investors make decisions. The analysis showed that how much people rely on AI and their views on technical problems greatly affect how they compare and judge AI decisions. This matches previous ideas about automation bias and how systems can be vulnerable. The study shows that investors do not evaluate AI decisions on their own, but rather through a mix of behavior and technology, where feelings of trust, reliability, and rationality come together. The study achieved its goal of showing the harmful effects of using AI without critical thinking. It shows that while AI can make things more efficient, using it without proper oversight can create hidden dangers that undermine investor confidence and the quality of their decisions.

An interesting and new finding is that when people think AI is "reasonable," it actually makes them less willing to trust it. This aligns with theories that say people mistakenly think algorithms are rational, even though their decisions are hard to understand and based on simple rules. So investors cast doubt on the idea that humans and machines work perfectly together. The study also found that while panic is a significant idea in behavioral finance, it does not significantly affect how people judge AI at the individual level. This suggests that concerns about trust in the system are more important than emotional reactions in situations involving technology. These results support the idea of combining behavioral finance with technical systems, showing how psychology and technology together influence decision-making.

Overall, this study adds to the global discussion about the negative side of AI by showing objective evidence that links the extent to which investors rely on AI, technical problems, doubt about rationality, and

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fragile trust to the outcomes of their decisions. The research shows that the risks of using AI are not just about technology, but also about human behavior. The findings support the idea that regulators, organizations, and investors need to go beyond simply liking automation and carefully examine its unexpected outcomes. In this way, the study helps both academic research and real-world understanding by showing that using AI without careful thought can make decision-making processes it has meant to improve worse.

5.2 Recommendations

Based on the findings, the first suggestion is the need for swift action to create rules and safety measures to address the dangers of adopting AI in finance without careful thought. Government leaders should establish global standards to ensure that AI systems are transparent, responsible, and easy to understand. This will help prevent technical mistakes and stop investors from being tricked by AI outputs that seem bright but are hard to understand. Banks and financial companies should help by thoroughly testing their AI tools, checking for any unfair advantages or biases, and putting in place ways for people to review and check AI decisions. This helps reduce the risks of relying too much on AI. By ensuring AI is well-managed, the financial market can remain stable, and investors can trust the system more, even as AI technology continues to evolve rapidly.

The second suggestion is to help investors learn more and become more aware. Since AI significantly affects decision-making, investors need to learn to think critically about what AI suggests, rather than just taking it for granted. Training should explain both the benefits and drawbacks of using AI, so investors can evaluate AI predictions and understand potential risks. By improving knowledge and fostering a mindset of careful thinking, investors can avoid relying too much on AI, retain control over their decisions, and ensure AI strengthens their financial situation, not weakens it. Together, these ideas ensure that using AI in finance is done in a balanced, careful, and lasting way, keeping investors and the market safe from the risks found in this study.

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Ethics approval

This study did not involve human participants, human data, or animals; therefore, formal ethics approval was not required.

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Availability of Data and Materials

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request (all raw sources are publicly cited in the manuscript).

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