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Understanding Investor Behavior: A Mixed-Methods Approach to Analyze Behavioral Factors Impacting Systematic Risk over Time

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Abstract

Purpose: Addressing a critical gap in financial research, this study explores the complex interplay between investor behavior and systematic risk over time. Understanding this relationship is crucial for effective risk management and financial decision-making in increasingly volatile markets. This study aims to identify key behavioral factors influencing investor decisions and empirically validate their impact on systematic risk fluctuations.

Methodology: A mixed-methods approach was employed. The qualitative phase utilized systematic review and meta-synthesis techniques to extract key behavioral indicators. Subsequently, a quantitative study involving 384 participants (investors, capital market professionals, and financial analysts) was conducted. Data were analyzed using structural equation modeling (SEM) with factor analysis in AMOS software.

Findings: The research identified six critical dimensions shaping investor behavior: individual, personality-related, social, psychological, emotional, and ethical components. These dimensions were ranked by their significance in influencing investment decisions. Empirical results confirmed all research hypotheses, highlighting the substantial impact of these behavioral dimensions on systematic risk.

Conclusion: This study provides nuanced insights into the dynamic relationship between investor behavior and systematic risk. By integrating qualitative and quantitative methodologies, we not only uncovered key behavioral dimensions but also statistically validated their influence on risk. These findings underscore the importance of considering behavioral factors in financial modeling, risk assessment, and policy-making. They offer valuable implications for financial professionals, regulators, and investors in developing more robust strategies for navigating complex financial landscapes.

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Introduction

In today's complex and dynamic world, financial markets play a vital role in the global economy. These markets, which mirror economic activities and investor expectations, are constantly influenced by various factors. Among these factors, investor behavior is of particular importance (Phan et al., 2023). A deep understanding of investor behavior and its impact on systematic risk, known as the undiversifiable risk, is crucial for effective capital management and financial decision-making in today's volatile markets (Fiordelisi et al., 2024).

Systematic risk, sometimes referred to as market risk, is an integral part of any investment. Unlike unsystematic risk, this type of risk cannot be eliminated through diversification and is related to macroeconomic, political, and social factors (Kostopoulos et al., 2022). However, what has received less attention is the role of investor behavior in shaping and changing this risk over time (Pilatin & Dilek, 2024).

Investor behavior, influenced by multiple individual, personality-related, social, psychological, emotional, and ethical factors, can significantly affect market fluctuations and, consequently, systematic risk. For instance, emotional reactions to economic news, herd behavior in buying or selling stocks, and decision-making based on cognitive biases can all lead to dramatic changes in prices and increased market volatility (Back et el., 2023).

The importance and necessity of this research can be examined from several perspectives. First, in the current era where financial markets are changing at an unprecedented pace, a deeper understanding of the factors affecting systematic risk can contribute to better capital management and potential loss reduction. Second, given the increasing complexities in financial markets and the emergence of new technologies such as algorithmic trading, examining the role of human behavior in shaping market risk has become more important. Third, this study can assist policymakers and regulatory bodies in formulating more effective laws and regulations to maintain market stability.

Despite the importance of the subject, there is a significant research gap in examining the dynamic relationship between investor behavior and systematic risk. Most previous studies have either focused on specific aspects of investor behavior or examined systematic risk statically (Zhang et al., 2024). However, the relationship between these two concepts is dynamic and variable over time. Furthermore, many previous studies have used purely quantitative or qualitative methods (Han et al., 2022), which can lead to an incomplete understanding of the complexities of this relationship.

The innovation of this research is observable in several dimensions. First, this study, using a mixed-method approach, attempts to provide a comprehensive and multidimensional picture of the relationship between investor behavior and systematic risk. The use of qualitative methods to identify key behavioral factors and then quantitatively validate these factors allows for a deeper and more accurate understanding of this relationship. Second, this research examines the impact of investor behavior on systematic risk over time, which is a dynamic and innovative approach in this field. Third, by considering a wide range of behavioral factors (individual, personality-related, social, psychological, emotional, and ethical), this study provides a comprehensive framework for better understanding the complexities of investor behavior.

The contribution of this research to the field of finance and investment is significant. Firstly, by presenting a comprehensive model of behavioral factors affecting systematic risk, this research can help improve risk assessment and asset pricing models. Secondly, the findings of this study can assist investors in making more informed decisions and better managing their portfolios. Thirdly, this research can aid policymakers and regulatory bodies in designing more effective mechanisms to control market fluctuations and reduce systematic risk.

The main objective of this research is to identify and analyze key behavioral factors affecting investor decisions and empirically validate the impact of these factors on systematic risk fluctuations over time. To achieve this goal, this study intends to first extract key behavioral indicators using qualitative methods and then test the impact of these indicators on systematic risk using quantitative methods.

In pursuit of this objective, the main research question is posed as follows: How do investors' behavioral factors influence systematic risk fluctuations over time?

By addressing this question, this research aims to provide new insights into understanding the dynamics of financial markets and contribute to the development of more effective strategies for risk management and investment. Through the combination of qualitative and quantitative methods, this study strives to present a comprehensive and accurate picture of this complex relationship, with the hope that its results will significantly advance knowledge in the fields of behavioral finance and risk management.

1. Theoretical Background

1.1 Behavioral Finance Theories

Behavioral finance theories represent a significant departure from traditional finance theories by acknowledging that investors are not always rational actors. These theories integrate psychological insights into financial decision-making, recognizing that cognitive biases, emotional responses, and social factors influence individual behavior. This paradigm shift aims to explain financial market anomalies that classical financial models struggle to elucidate (Rahnama Roodposhti & Zandie, 2011).

• Prospect Theory and Loss Aversion: Developed by Daniel Kahneman and Amos Tversky, prospect theory forms the cornerstone of behavioral finance. This theory posits that individuals evaluate potential outcomes relative to a reference point and are more sensitive to losses than to equivalent gains. This asymmetry significantly shapes decision-making, influencing risk preferences and choices (Harrison & Swarthout, 2023).

• Mental Accounting and Framing: Mental accounting involves the cognitive process of categorizing and evaluating financial decisions, which can impact spending and investment choices. Framing examines how the presentation of information can influence decisions. Notably, the same information presented differently may lead to divergent choices (Liu & Chiu, 2015).

• Overconfidence and Herding Behavior: Overconfidence refers to individuals' tendency to overestimate their abilities, which can significantly affect transactional behaviors. Herding behavior examines the inclination to follow the crowd, even when it conflicts with rational analysis, often leading to market bubbles or crashes (Purwidianti et al., 2023).

• Anchoring and Confirmation Bias: Anchoring occurs when individuals rely heavily on the first piece of information they encounter, which subsequently influences their judgments. Confirmation bias involves favoring information that confirms pre-existing beliefs, potentially amplifying cognitive errors (Lieder et al., 2017).

1.2 Systematic Risk

Systematic risk, also known as market risk, encompasses factors that affect the entire market rather than individual securities. It includes events such as economic downturns, interest rate fluctuations, or geopolitical crises. Quantifying systematic risk involves measures such as beta, which gauges an asset's sensitivity to market movements. Beta helps investors evaluate an asset's risk in relation to the broader market. Sources of systematic risk include economic factors, interest rate changes, and geopolitical events. Types of systematic risk include market risk, interest rate risk, currency risk, and inflation risk. Understanding these sources is vital for effective risk management (Ren et al., 2022).

1.3 Investor Behavior Models

To understand investor behavior, various models have been developed to illuminate the decision-making processes that drive financial choices. These models range from traditional rational frameworks to those rooted in behavioral finance, acknowledging the complexities of human cognition and emotion (Almeida & Gonçalves, 2023). The following are key investor behavior models:

• Rational Choice Theory: This theory serves as a fundamental framework in classical economics, positing that individuals make decisions to maximize their utility by weighing costs and benefits. In finance, this theory assumes that investors, acting as rational agents, carefully evaluate available information to make decisions that optimize their portfolios. This model presumes that individuals act in their own self-interest, seeking to achieve the highest level of satisfaction given their available resources (Kari, 2016).

• Bounded Rationality: Contrary to the assumptions of rational choice theory, bounded rationality recognizes the inherent cognitive limitations in decision-making. This model, proposed by Herbert Simon, suggests that people's information processing is often constrained by time, cognitive capacity, or decision complexity. Bounded rationality acknowledges that individuals may use heuristics or rules of thumb to simplify complex choices, deviating from the ideal rational decision-maker often assumed in traditional economic models (Yun et al., 2022).

• Prospect Theory in Decision-Making: As a cornerstone of behavioral finance, prospect theory diverges from traditional utility theory. Developed by Daniel Kahneman and Amos Tversky, this model examines how people make decisions and evaluate potential gains and losses. Unlike classical economics, prospect theory introduces the concept of loss aversion, suggesting that people are more sensitive to losses than equivalent gains. By incorporating psychological and emotional dimensions of risk, this theory provides a more realistic picture of decision-making under uncertainty (Tian et al., 2022).

• Behavioral Portfolio Theory: This theory recognizes that investor decisions may be influenced by cognitive biases and emotional responses. Developed by Hersh Shefrin and Meir Statman, behavioral portfolio theory integrates behavioral factors into portfolio construction. It departs from the premise of purely rational decision-making, acknowledging that investors may deviate from traditional models due to psychological factors. Thus, behavioral portfolio theory provides a lens through which to understand how behavioral considerations affect the composition and management of investment portfolios (Lukomnik & Hawley, 2021).

2. Literature Review

Recent studies have significantly contributed to our understanding of investor behavior and its impact on financial markets. This section reviews key empirical findings that inform our research.

Asemi et al. (2023) developed a model using customer investment service feedback and neuro-fuzzy inference solutions to generate personalized investment recommendations. Their system considers seven factors, including demographic data and investment types, to support the investment process for customers and potential investors.

Rosyidah and Pratikto (2022) identified seven behavioral biases through trend analysis: exploratory bias, self-documentation bias, framing bias, herd bias, aversion bias, tendency effect, and overconfidence bias. These biases provide a theoretical framework for understanding investor behavior.

Wang et al. (2022) examined the impact of investment behavior on financial markets during the COVID-19 pandemic. Their results revealed that COVID-19 uncertainty significantly moderated the relationship between risk perception and both general and financial risk tolerance. They also found that profitability rates affected risk tolerance, and risk perception significantly influenced financial risk tolerance.

Isidore and Christie (2019) explored the relationship between investors' annual earnings and eight behavioral biases. They found that investors with higher annual earnings were generally less susceptible to biases, except for overconfidence. Higher-earning investors showed more overconfidence but less representativeness, loss aversion, availability, and mental accounting biases.

Zahera and Bansal (2018) described various biases in investment decision-making within behavioral finance. They emphasized the emerging importance of understanding human emotions and behavior in financial markets, suggesting that companies, policymakers, and securities issuers should consider investor sentiment before market issuance.

Kumar and Goyal (2016) examined the relationship between rational decision-making and behavioral biases among individual investors in India. They found that while investors generally follow a rational decision-making process, behavioral biases arise at different stages. Gender and income significantly influenced the decision-making process, with male investors more prone to overconfidence and herding biases.

Nemati and Rahmani Noroozabad (2023) investigated the effect of psychological biases on the financial satisfaction of investors in the Tehran Stock Exchange. They found that overconfidence, reliance on financial experts, money categorization tendencies, budgeting tendencies, adaptation tendencies, social responsibility, spousal reliance, and self-control positively influenced financial satisfaction.

Rahimpour Khanghah et al. (2021) studied the effects of self-control and financial knowledge on investors' financial satisfaction, mediated by financial behavior. Their results showed that self-control and financial knowledge directly affect investors' financial behavior, which in turn positively influences financial satisfaction.

Saadat Zadeh Hesar et al. (2022) investigated the relationship between cognitive bias in investors' behavior and stock price fluctuations. They found that cognitive biases decrease in low volatility conditions, reducing their impact on investor behavior. Conversely, biases increase in high volatility conditions, negatively impacting investor behavior and increasing the probability of mistakes.

Asiabi-Aghdam et al. (2020) examined stock asset portfolio selection based on behavioral economics. Their research revealed that overconfidence significantly influences investors' decision-making.

Jafari et al. (2020) studied the role of psychological and functional factors in stock market investment willingness, mediated by investor satisfaction and perceived risk. Their results indicated that perceived risk and investor satisfaction effectively mediate the relationship between psychological factors and performance.

This literature review underscores the complex interplay of psychological, cognitive, and external factors in shaping investor behavior and market dynamics, providing a solid foundation for our current study.

3. Research Method

This study employs a mixed-methods approach, combining qualitative and quantitative methodologies to provide a comprehensive understanding of the relationship between investor behavior and systematic risk. The research design comprises two main phases: a qualitative meta-synthesis followed by a quantitative survey and analysis.

3.1 Qualitative Phase: Meta-Synthesis

The qualitative phase utilizes Sandelowski and Barroso's (2007) meta-synthesis approach to systematically review and synthesize existing qualitative research on investor behavior and systematic risk. This method was chosen for its rigorous and systematic nature, allowing for a comprehensive integration of findings from multiple qualitative studies.

The meta-synthesis process consisted of seven sequential steps:

1. Formulating the research question and objectives
2. Conducting a systematic literature review
3. Searching and selecting relevant articles
4. Extracting information and results from reviewed articles
5. Analyzing and synthesizing qualitative findings
6. Implementing quality control measures
7. Presenting the results

To ensure the validity and reliability of the meta-synthesis, several measures were implemented:

- Descriptive validity: We established clear criteria for article selection, conducted weekly progress review meetings, and utilized EndNote software for efficient article management.
- Interpretive validity: Weekly meetings were held to discuss and review the research team's interpretations of the findings.
- Theoretical validity: An expert in the field of behavioral finance was consulted to validate the theoretical frameworks emerging from the synthesis.
- Pragmatic validity: All stages of the research process were verified by the research team and external experts.

The reliability of the meta-synthesis was further ensured through the application of the Critical Appraisal Skills Programme (CASP, 2018). This involved a rigorous evaluation of the selected articles based on ten parameters, including clarity of research objectives, methodological logic, and ethical considerations.

3.2 Quantitative Phase: Survey and Structural Equation Modeling

Building on the findings from the meta-synthesis, we developed a quantitative survey to empirically test the identified behavioral factors and their impact on systematic risk.

A structured questionnaire was developed based on the key behavioral dimensions identified in the meta-synthesis. The questionnaire utilized a 5-point Likert scale to measure respondents' attitudes and behaviors. The survey was distributed to a sample of investors, capital market professionals, and financial analysts.

Given the undefined size of the target population, we employed a non-probability sampling technique, specifically convenience sampling. The sample size was determined using Cochran's formula, resulting in 384 participants. This sample size ensures a confidence level of 95% with a margin of error of 5%, which is standard in social science research.

To ensure the reliability of the quantitative data, Cronbach's alpha coefficient was calculated for each construct in the questionnaire. A threshold of 0.7 was set as the minimum acceptable value, in line with standard practice in social science research. For construct validity, we employed confirmatory factor analysis (CFA) using structural equation modeling (SEM) in AMOS software.

The quantitative data analysis consisted of several steps:

1. Descriptive statistics to summarize the demographic characteristics of the sample and provide an overview of the responses.

2. Confirmatory Factor Analysis (CFA) to validate the measurement model and ensure that the observed variables adequately represent the latent constructs identified in the meta-synthesis.

3. Structural Equation Modeling (SEM) to test the hypothesized relationships between the behavioral factors and systematic risk. SEM was chosen for its ability to simultaneously examine multiple dependent and independent variables, as well as to model latent constructs.

4. Model fit assessment using various indices such as Chi-square/df ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) to ensure the adequacy of the proposed model.

5. Path analysis to examine the direct and indirect effects of behavioral factors on systematic risk.

This comprehensive methodological approach allows for a robust examination of the complex relationship between investor behavior and systematic risk. By combining qualitative meta-synthesis with quantitative empirical testing, we aim to provide a nuanced and validated understanding of this critical aspect of financial markets.

4. Research Findings

4.1 Data Analysis in the Qualitative Section

A systematic and comprehensive review of qualitative research findings was conducted based on the research objectives. The keywords used for searching included "investor behavior," "behavioral finance," "financial decision making," "investor psychology," "financial behavior," and "systematic risk." These searches were conducted in titles, abstracts, and keywords of published articles.

The inclusion criteria for the research were:

1. Non-Persian qualitative articles related to the research question

2. Published in databases including Emerald, Science Direct, Springer, Web of Science, and Google Scholar between 2014 and 2023

3. Indexed by Scopus, ISI-Listed, or ISI-WOS

Additionally, Persian qualitative articles related to the research question, published in reputable scientific research journals during the specified period, freely accessible, and indexed by databases including Magiran, SID, and Civilica, were also included in the review.

To increase the validity of the research, the inclusion criteria led to the exclusion of non-reviewed documents such as books and theses, as well as articles with questionable citations. The frequency of articles in Persian and non-Persian databases is presented in Table 1.

According to Table 1, 292 primary articles were identified in the databases. The application of inclusion criteria resulted in the removal of 256 articles, leaving 36 articles related to the research question. The selection process is presented in Table 2.

Using the comparative evaluation method of Sandelowski and Barroso (2007), the final articles were evaluated based on parameters including authors' specifications, year of publication, article title, purpose, methodology, analysis, and findings. The quality of the articles was evaluated and scored based on the Critical Appraisal Skills Programme (2018). This method was applied to all final articles reviewed in the research background. The frequency of articles with an excellent score (41-50) was 81%, and those with a very good score (31-40) was 19%, indicating the high quality of the final articles.

Table 1: Articles' frequency in databases

Database	Total Frequency	Final articles' frequency
Emerald	63	5
Science Direct	58	6
Springer	65	4
Web Of Science	32	6
Google Scholar	56	11
Magiran	8	3
SID (Scientific Information Database)	4	1
Civilica	6	0
total	292	36

Table 2: The method of selecting final articles

Steps	Number of reviewed articles	Number of removed articles	Reasons for remove articles
Keywords search in databases	Inclusion of 292 articles and examined the title	Output of 83 articles	Unrelated title. The magazine wasn't index
Examining the articles selected in the previous step	Inclusion of 209 articles and examined the abstract	Output of 116 articles	Unrelated objective. Non-qualitative method
Examining the articles selected in the previous step	Inclusion of 93 articles and examined the findings	Output of 57 articles	Unrelated objective. Non-qualitative method. Unrelated findings
Examining the articles selected in the previous step	Inclusion of 36 articles and consultation for theoretical consensus	Output of 0 article	
Number of final articles	Inclusion 0f 36 articles related to the reseach's objective		

Within the framework of Sandelowski and Barso's method, the results of the final papers were analyzed through a taxonomic analysis approach, which includes inductive analysis using open, axial, and selective coding. This method provides a better understanding of concepts and forms the basis for extracting categories.

Initially, expressions related to investor behavior were extracted as primary codes. Then, through open coding, primary codes were identified as concepts representing the resulting patterns as subcomponents. Finally, subcomponents were classified as components and then as dimensions using axial coding to identify semantic relationships. Table 3 shows the identified dimensions and components, as well as the references and frequency of the subcomponents.

Table 3: Open and axial coding of extracted data

<table>
<tr><th>Dimensions</th><th>Components</th><th>Concepts</th><th>References</th></tr>
<tr><td rowspan="3">Individual Components</td><td>Risk aversion</td><td>Loss aversion. Ambiguity aversion. Risk tolerance. Risk perception</td><td>Smaga (2014). Dadres et al. (2018). Battistini et al. (2014)</td></tr>
<tr><td>Overconfidence</td><td>Illusion of control. Optimistic bias. Dunning-Kruger Effect. Confirmation bias</td><td>Kent & Hirshleifer (2015). Mensi et al. (2017)</td></tr>
<tr><td>Information processing</td><td>Cognitive biases. Information overload. Mental shortcuts. Information bias</td><td>Gheisari et al. (2021). Almeida & Gonçalves (2023)</td></tr>
</table>

	Decision-making styles	Prospect theory. Behavioral economics. Heuristics. Bounded rationality	Mansi et al. (2017). Almeida & Gonçalves (2023)
	Fiscal knowledge	Familiarity bias. Financial literacy. Knowledge gap. Expertise	Gheisari et al. (2021). Zahera & Bansal (2018).
	Investment experience	Future bias. Learning curve. Experience effect. Past performance bias	Zahera & Bansal (2018). Shaik et al. (2022).
	Time priority	Present bias. Future discount. Time horizon. Delay discount	Zahera & Bansal (2018) Shaik et al. (2022).
	Wealth perception	Interruption effect. Illusion of wealth. Relative deprivation. Attitude towards money	Dadres et al. (2018). Manocha et al. (2023)
Emotional Components	Fear	Anxiety, panic, fear of missing out (FOMO). loss aversion	Shahzad et al. (2018). Manocha et al. (2023)
	Cupidity	Envy, euphoria, excessive trading, speculative bubbles	Kiruba & Vasantha (2021). Mestre (2021)
	Excitement	Euphoria, excessive optimism, market enthusiasm, speculation	Shahzad et al. (2018). Kiruba & Vasantha (2021).
	Regret	Regret, regret aversion, result bias, counterfactual thinking	Kumar & Goyal (2015). Mestre (2021)
	Hope	Optimism, wishful thinking, positive outcome expectations, expectation bias	Kumar & Goyal (2015). Khawaja & Alharbi (2021)
	Panic	Hopelessness, market crash, herd behavior, scary sale	Derbali & Hallara (2016). Khawaja & Alharbi (2021)
	Euphoria	Excessive excitement, irrational exuberance, bubble psychology, mania	Derbali & Hallara (2016). Shaik et al. (2022).
	Disillusionment	Hopelessness, Disillusionment aversion, loss chasing, emotional reaction	Metawa et al. (2019). Shaik et al. (2022).
Psychological Component	Cognitive dissonance	Belief persistence, confirmation bias, attitude change, rationalization	Nemati and Rahmani-Noroozabad (2023). Rajasekar et al. (2023)
	Mental accounting	Anchoring, framing effect, mental separation, budget bias	Metawa et al. (2019). Isidore & Christie (2019)
	Confirmation bias	Availability heuristics, selective perception, biased interpretation, anchoring	Nemati and Rahmani Noroozabad (2023). Isidore & Christie (2019)
	Self-control	Impulsivity, delayed gratification, willpower, resistance to temptation	Cherono et al. (2019). Rajasekar et al. (2023)
	Attention bias	Selective attention, attention biases, salience, information filtering	Isidore & Christie (2019). Gurbaxani & Gupte (2021)
	Mental persistence	Resilience, emotional regulation, stress management, coping strategies	Cherono et al. (2019). Gurbaxani & Gupte (2021)
	Behavioral biases	Think tank, cultural bias, the blind spot of bias, heuristic representation	Nemati and Rahmani Noroozabad (2023). Xi et al. (2020)
Moral Components	Moral values	Honesty, ethical dilemmas, ethical reasoning, ethical decision making	Ghayour Baghbani & Behboudi (2017). Xi et al. (2020)
	Altruism	Generosity, social behavior, reciprocity, empathy	Hernández et al. (2019). Chaudhry & Kulkarni (2021)
	Fairness	Mutual fairness, distributive justice, equality theory, neutrality	Kengatharan & Kengatharan (2014). Chaudhry & Kulkarni (2021)
	Social responsibility	Humanitarianism, corporate social responsibility, sustainable investment, social impact assessment	Hernández et al. (2019). Singh et al. (2020)
	Honesty	Trustworthiness, transparency, honesty, loyalty	Ngoc (2014). Wang et al. (2022)
	Empathy	Compassion, emotional empathy, perspective, empathic concern	Ngoc (2014). Wang et al. (2022)
	Conscientiousness	Virtue ethics, conscientious behavior, duty, moral development	Kengatharan & Kengatharan (2014). Singh et al. (2020)

Social Components	Peer influence	Social pressure, conformity, peer effects, normative influence	Asemi et al. (2023) Rajasekar et al. (2023)
	Social networks	Information cascades, social capital, network analysis, social communication	Faridniya & Faridnia (2019). Khawaja & Alharbi (2021)
	Social Capital	Reputation, trust networks, social connections, social participation	Asemi et al. (2023). Khawaja & Alharbi (2021)
	Cultural influences	Cultural norms, cultural sensitivity, cultural intelligence, intercultural psychology	Kovács et al. (2021). Wang et al. (2022)
	Communication patterns	Media influence, information dissemination, communication styles, persuasion	Kovács et al. (2021) Wang et al. (2022)
	Community participation	Participation in social causes, community participation, civic participation, social activism	Faridniya & Faridnia (2019). Rajasekar et al. (2023)
Personality Components	Openness to experience	Novelty, creativity, open mind, intellectual curiosity	Ghayour Baghbani & Behboudi (2017). Mestre (2021)
	Conscientiousness	Regularity, goal-oriented, self-discipline, reliability	Kumar & Goyal (2016). Asemi et al. (2023).
	Extroversion	Sociability, decisiveness, energy, extroversion	Kumar & Goyal (2016). Mestre (2021)
	Agreeableness	Cooperation, compassion, empathy	Baker et al. (2019). Asemi et al. (2023).
	Neuroticism	Emotional stability, resilience, tendency to anxiety, emotional reaction	Baker et al. (2019). Cherono et al. (2019).
	Willingness to take risks	Risk tolerance, risk-taking behavior, risk perception, risk-taking	Smaga (2014). Battistini et al. (2014)
	Locus of control	Internal control versus external control, self-determination, beliefs of control, autonomy	Cherono et al. (2019). Kovács et al. (2021)
	Self-efficacy	Self-confidence in decision-making, mastery, self-belief, confidence in specific work	Kent & Hirshleifer (2015). Kovács et al. (2021)

4.2 Data Analysis in the Quantitative Section

In the quantitative section, we investigated the statistical indicators and normality of the research data through tests of skewness and kurtosis using SPSS software. We ensured the validity of the data through confirmatory factor analysis, path analysis, and fitting to the research conceptual model. Hypothesis testing was conducted using structural equation modeling with Amos software.

The average for all indicators in this study is above 3, indicating a high degree of agreement among respondents on the validity of the indicators. Furthermore, the skewness and kurtosis coefficients of all indicators fall within the range of -3 to +3, suggesting that the data distribution is normal.

The research measurement model was estimated through the implementation of confirmatory factor analysis, which is presented in Figure 1 in the estimation mode of standard coefficients.

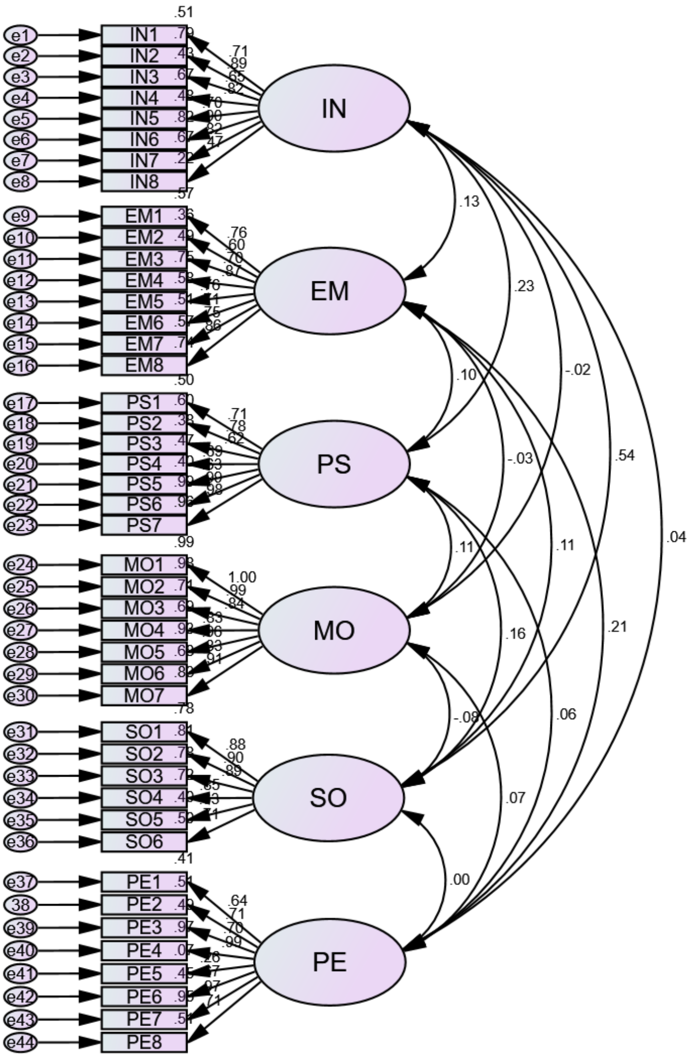

Figure 1. Measurement model in estimating standard coefficients

In confirmatory factor analysis, two conditions must be met for each question to remain in the model. First, the factor loading of the question must be greater than 0.5, and second, it should be significant, i.e., the t-value must be greater than 1.96 in absolute value (Hair et al., 2006). In this study, based on the results from Amos software, indicators IN4 and PE5 were removed from the model as they did not meet the minimum desirability level of loading and significance. The results of the modified measurement model after removing these two indicators with weak factor loading and lack of significance are presented in Table 4.

Results of composite reliability, convergent validity, and divergent validity are presented in Table 5. The average variance extracted (AVE) and composite reliability (CR) calculated for all variables in the measurement model were greater than 0.5 and 0.7, respectively. Additionally, AVE is greater than 0.5 for all model constructs, and CR is greater than AVE in all cases (CR>AVE). Therefore, convergent validity and composite reliability of the research instrument were confirmed. Considering that the value of AVE for each variable was greater than both the average squared shared variance (ASV) and the maximum squared shared variance (MSV) among all variables in the measurement model, the divergent validity of the research tool was also confirmed.

Table 4: Results of Confirmatory Factor Analysis after Model Modification

Factor	Code	Factor load	t-value	Factor	Code	Factor load	t-value
Indiv	IN1	.712	15.581	Moral C	MO1	.995	65.789

	IN2	.891	21.538		MO2	.988	61.308
	IN3	.654	13.960		MO3	.843	28.067
	IN4	.820	18.985		MO4	.829	26.724
	IN5	.696	15.132		MO5	.963	-
	IN6	.904	22.018		MO6	.827	26.568
	IN7	.819	-		MO7	.911	36.760
Emotional Components	EM1	.758	15.360	Social Components	SO1	.885	14.227
	EM2	.600	11.826		SO2	.900	14.401
	EM3	.699	14.006		SO3	.886	14.241
	EM4	.868	17.975		SO4	.846	13.777
	EM5	.759	-		SO5	.635	-
	EM6	.711	14.276		SO6	.708	12.024
	EM7	.755	15.277	Personality Components	PE1	.638	12.469
	EM8	.863	17.850		PE2	.711	13.923
Psychological Components	PS1	.710	12.398		PE3	.702	13.740
	PS2	.776	13.295		PE4	.986	19.387
	PS3	.619	11.063		PE6	.668	13.062
	PS4	.687	12.066		PE7	.973	19.179
	PS5	.634	-		PE8	.714	-
	PS6	.994	15.875				
	PS7	.981	15.767				

Table 5: Results of composit reliability, convergent validity and divergent validity

Variable	CR	AVE	MSV	ASV	Result
Individual Components	0.919	0.621	0.277	0.068	Confirm
Emotional Components	0.913	0.572	0.044	0.016	Confirm
Psychological Components	0.916	0.616	0.049	0.020	Confirm
Moral Components	0.971	0.829	0.013	0.005	Confirm
Social Components	0.922	0.666	0.277	0.064	Confirm
Personality Components	0.914	0.610	0.044	0.011	Confirm

To confirm the fit of the model, two indices among X2/df, RMSEA, PNFI, and PCFI, which are called parsimony indices, must be within the permissible value range. At least one of the GFI and AGFI indices, known as absolute indices, must be within the permissible value range, and at least two indices among the remaining CFI, IFI, RFI, TLI, and NFI indices, which are called comparative indices, must be within the permissible value range. The results of measuring the fit of the measurement model are presented in Table 6, and as can be seen, the measurement model demonstrates a good fit. The structural model of the study in standard coefficient estimation mode is shown in Figure 2.

According to the output of the Amos software, Table 7 shows that all the significant coefficients between the factors are greater than the absolute value of 1.96, indicating that all 6 identified components have a significant impact on investors' behavior.

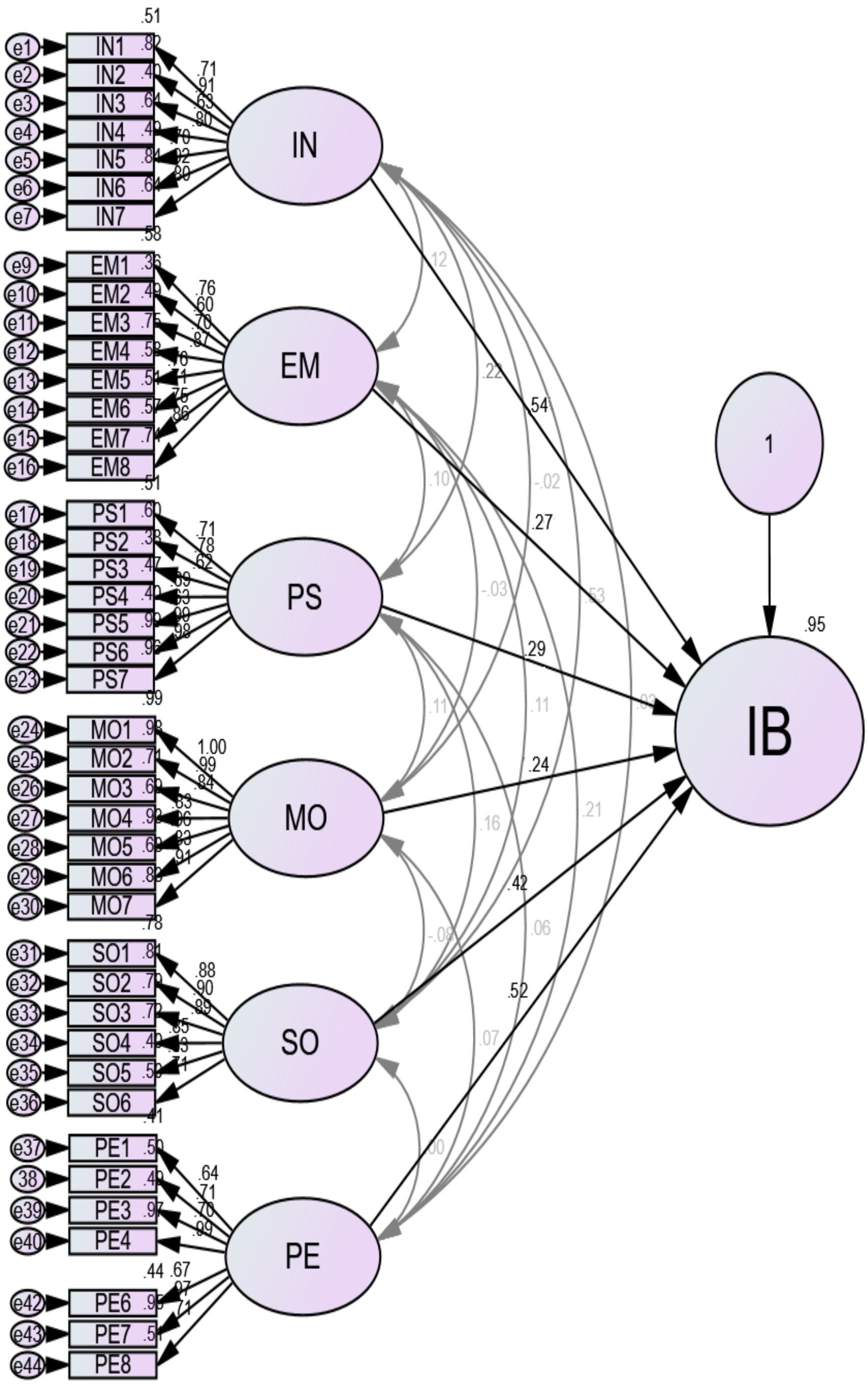

Figure 2. Structural model in mode of estimating standard coefficients

Table 6: The results of fitting the research model

Fit indices	Permissible Value	Results of Measurement Model
X2/df	Less than 3	2.765
RMSEA	Less than 0.1	0.063
PNFI	More than 0.5	0.783
PCFI	More than 0.5	0.810
GFI	More than 0.8	0.802
CFI	More than 0.9	0.938
TLI	More than 0.9	0.928
IFI	More than 0.9	0.938

Table 7. The results of research hypotheses test

Category	Hypotheses	t-value	P-value	Path Coefficient
1	Individual components→ Investor's behavior	4.116	***	0.54
2	Emotional components→ Investor's behavior	3.984	***	0.27
3	Psychological components → Investor's behavior	3.303	***	0.29
4	Moral components → Investor's behavior	3.216	***	0.24
5	Social components→Investor's behavior	3.329	***	0.42
6	Personality components → Investor's behavior	4.23	***	0.52
*** means p<0.01				

5. Discussion and Conclusion

The intricate relationship between investor behavior and systematic risk has long been a critical area of study in financial markets. As markets become increasingly complex and volatile, understanding the multifaceted dimensions that shape investor behavior and their subsequent impact on systematic risk over time has become paramount. This research addresses a significant gap in the literature by providing a comprehensive analysis of the behavioral factors influencing investor decisions and their empirical validation in the context of systematic risk fluctuations. The importance of this study lies in its potential to enhance risk management strategies, improve financial decision-making processes, and contribute to more stable and efficient financial markets.

To achieve these objectives, this study employed a mixed-methods approach, combining qualitative meta-synthesis with quantitative empirical analysis. The qualitative phase involved a systematic review and synthesis of existing literature, identifying key behavioral indicators. This was followed by a quantitative study utilizing structural equation modeling (SEM) to validate and quantify the impact of these behavioral factors on systematic risk. The results revealed six primary dimensions shaping investor behavior: individual, personality-related, social, psychological, emotional, and ethical components. These dimensions, comprising 42 distinct factors, were found to have varying degrees of influence on investor behavior and, consequently, on systematic risk. The individual components emerged as the most influential, followed closely by personality-related factors, highlighting the complex interplay between personal characteristics and market dynamics in shaping risk patterns.

The emergence of individual components as the most influential dimension (path coefficient 0.54) underscores the critical role of personal characteristics in shaping investment decisions. This finding aligns with and extends previous research by providing a more nuanced understanding of how individual factors interact to influence investor behavior. Risk aversion, identified as a dominant factor, corroborates the work of Smaga (2014) and Battistini et al. (2014), who emphasized its importance in financial decision-making. However, our study goes further by contextualizing risk aversion within a broader framework of individual traits. The significant impact of overconfidence, as highlighted by Kent and Hirshleifer (2015), is reinforced in our findings, suggesting that this bias continues to play a crucial role in modern investment landscapes. Our research innovates by integrating factors such as information processing and decision-making styles into the individual dimension. This approach provides a more holistic view of how investors' cognitive processes influence their behavior, extending beyond the traditional focus on risk attitudes. The inclusion of fiscal knowledge as a significant factor builds on the work of Gheisari et al. (2021), emphasizing the importance of financial literacy in today's complex markets.

The strong influence of personality components (path coefficient 0.52) on investor behavior represents a significant contribution to the field. While previous studies such as Kumar and Goyal (2016) and Asemi et al. (2023) have explored individual personality traits, our research provides a more comprehensive framework by examining how these traits interact within the investment context. The identification of openness to experience, conscientiousness, extroversion, and agreeableness as key factors aligns with the Big Five personality model, widely recognized in psychological research. However, our study innovates by specifically relating these traits to investment behavior, offering a bridge between psychological theory and financial practice. The inclusion of neuroticism and willingness to take risks as significant factors builds upon the work of Baker et al. (2019) and Cherono et al. (2019), providing a more nuanced understanding of how emotional stability and risk propensity influence investment decisions. Our findings on locus of control and self-efficacy extend the work of Kent and Hirshleifer (2015) and Kovács et al. (2021), highlighting the importance of perceived control and confidence in financial decision-making.

The significant impact of social components (path coefficient 0.42) on investor behavior underscores the importance of social influences in financial markets. This finding aligns with previous research but offers a more comprehensive view of how various social factors interact to shape investor decisions. Our analysis of peer influence builds upon the work of Asemi et al. (2023) and Rajasekar et al. (2023), but goes further by exploring how this influence operates within broader social networks and social capital structures. This approach provides a more contextual understanding of peer effects, considering the complex web of social relationships that investors navigate. The inclusion of cultural influences and communication patterns as significant factors extends the work of Kovács et al. (2021) and Wang et al. (2022), offering insights into how broader societal norms and information flows impact investment behavior. Our focus on community participation as a key factor represents an innovative approach, highlighting the role of collective dynamics in shaping individual investment decisions.

The identification of psychological components as a significant dimension (path coefficient 0.29) aligns with the growing body of behavioral finance literature. However, our research provides a more comprehensive framework for understanding how various psychological factors interact to influence investor behavior. Our findings on cognitive dissonance corroborate the work of Nemati and Rahmani Noroozabad (2023) and Rajasekar et al. (2023), but we extend this understanding by examining how cognitive dissonance interacts with other psychological factors such as mental accounting and confirmation bias. This integrated approach offers a more nuanced view of the cognitive processes underlying investment decisions. The inclusion of attentional bias and mental persistence as significant factors represents an innovative contribution to the field, building upon the work of Isidore and Christie (2019) and Gurbaxani and Gupte (2021). By considering these less-studied psychological aspects, our research provides a more complete picture of the cognitive landscape influencing investor behavior.

The significant influence of emotional components (path coefficient 0.27) on investor behavior aligns with previous research highlighting the role of emotions in financial decision-making. However, our study provides a more comprehensive framework for understanding how various emotions interact to shape investment choices. Our analysis of fear, greed, excitement, and regret as key factors builds upon the work of Shahzad et al. (2018) and Manocha et al. (2023), but goes further by examining how these emotions interact with other factors such as hope, panic, and euphoria. This integrated approach offers a more nuanced understanding of the emotional landscape influencing investor behavior. The inclusion of disillusionment as a significant factor represents an innovative contribution, extending the emotional spectrum considered in investment behavior research. This addition provides insights into the long-term emotional impacts of market experiences on investor decision-making.

The identification of moral components as a significant dimension (path coefficient 0.24) represents an important contribution to the field of behavioral finance. While previous research has touched on ethical considerations in investment, our study provides a comprehensive framework for understanding how various moral factors interact to influence investor behavior. Our analysis of moral values, altruism, and fairness as key factors builds upon the work of Ghayour Baghbani and Behboudi (2017) and Xi et al. (2020), but extends this understanding by examining how these moral considerations interact with other factors such as social responsibility and empathy. This integrated approach offers a more holistic view of the moral landscape influencing investment decisions. The inclusion of honesty and conscientiousness as moral factors represents an innovative perspective, bridging the gap between personal integrity and financial decision-making. This approach aligns with but also expands upon the work of Kengatharan and Kengatharan (2014) and Wang et al. (2022), who explored the role of ethical considerations in investment behavior. Our findings on the impact of empathy in investment decisions contribute to a growing body of research on socially responsible investing, as highlighted by Hernández et al. (2019) and Chaudhry and Kulkarni (2021). However, our study innovates by placing empathy within a broader framework of moral components, providing a more nuanced understanding of how social consciousness influences investor behavior.

The consideration of social responsibility as a moral factor in investment decisions aligns with the increasing focus on ESG (Environmental, Social, and Governance) criteria in financial markets. Our research extends this understanding by examining how social responsibility interacts with other moral factors to shape investor behavior, offering insights into the complex decision-making processes of ethically-minded investors. In conclusion, our examination of moral components provides a more comprehensive and nuanced understanding of how moral considerations influence investment decisions. By integrating various moral factors and exploring their interactions, our study offers valuable insights into the ethical dimensions of investor behavior, contributing to both theoretical understanding and practical applications in the field of behavioral finance.

In conclusion, while our findings corroborate much of the existing literature, they also extend and integrate previous research in novel ways. By providing a comprehensive, multidimensional framework for understanding investor behavior, our study offers a more nuanced and contextual understanding of how various factors interact to influence investment decisions and, consequently, systematic risk. This holistic approach represents a significant innovation in the field of behavioral finance and offers valuable insights for both researchers and practitioners in the financial industry.

Building upon our findings, several practical implications and recommendations emerge for investors, financial professionals, and policymakers. These suggestions aim to bridge the gap between research insights and practical steps, fostering a more informed, resilient, and ethically-conscious investment environment.

For individual investors, our research underscores the importance of self-awareness and continuous education. Implementing educational programs aimed at enhancing investors' understanding of risk, particularly focusing on individual factors such as risk aversion, overconfidence, and decision-making styles, can help investors make more conscious decisions. This could include workshops, online courses, or accessible resources to improve financial literacy. Moreover, given the significant influence of personality components, investors should be encouraged to assess their own personality traits and understand how these might impact their investment decisions. This self-reflection could lead to more tailored investment strategies that align with individual personality profiles.

Financial professionals and advisors can leverage our findings to develop more personalized and effective client services. By integrating behavioral insights into their client interactions, advisors can tailor financial plans to match clients' cognitive and emotional tendencies, thereby improving adherence to long-term financial goals. Understanding the role of psychological factors such as cognitive dissonance and behavioral biases allows for the development of strategies to mitigate their negative impacts. Additionally, recognizing the importance of social components, financial institutions could create platforms that facilitate positive peer influence and knowledge sharing, such as community forums or investment clubs, providing investors with opportunities to learn from collective experiences.

Our research on emotional components highlights the need for strategies to manage the impact of emotions on investment decisions. Financial experts could implement emotional intelligence training programs, helping investors recognize and manage emotions like fear, greed, and excitement. These programs could include techniques for maintaining composure during market volatility and making rational decisions despite emotional pressures. Furthermore, the development of tools or apps that help investors track their emotional states in relation to their investment decisions could provide valuable self-awareness and learning opportunities.

The significance of moral components in our findings suggests an opportunity for the financial industry to align more closely with investors' ethical values. Companies and financial institutions should consider developing and promoting investment products that emphasize ethical values, fairness, and social responsibility. This could include expanding offerings in socially responsible investing (SRI) and environmental, social, and governance (ESG) focused funds. Moreover, transparency in corporate practices and clear communication about the ethical implications of various investment options could help investors make choices that align with their moral values.

For policymakers and regulators, our research underscores the need for a more nuanced approach to financial regulation that takes into account the behavioral aspects of investing. This could involve developing policies that protect investors from their own behavioral biases, such as mandatory cooling-off periods for significant investment decisions or requiring clearer disclosures about the psychological factors that might influence investment choices. Additionally, incorporating behavioral finance principles into financial education curricula at various levels of education could help cultivate a more informed and resilient investor base.

Lastly, our findings on the interplay between various behavioral dimensions highlight the importance of a holistic approach to investment strategy and risk management. Financial institutions and regulators should consider developing comprehensive risk assessment tools that account for not just financial metrics, but also behavioral factors. This could lead to more accurate risk profiling and better-tailored investment advice.

By implementing these recommendations, stakeholders in the financial industry can work towards creating a more stable, efficient, and ethically-aligned investment environment. These practical steps, grounded in our research findings, have the potential to enhance investment outcomes, reduce systematic risk, and foster a more robust and responsible financial ecosystem.

While our study provides valuable insights into the relationship between investor behavior and systematic risk, it is important to acknowledge several limitations that may impact the generalizability and interpretation of our findings. Firstly, the use of self-reported questionnaires, while common in behavioral research, may introduce social desirability bias and potential inaccuracies in participants' responses. Future studies could benefit from incorporating more objective measures of behavior, such as actual investment decisions or physiological responses to market stimuli.

Secondly, the cross-sectional nature of our study provides a snapshot of investor behavior at a specific point in time, limiting our ability to establish causal relationships or capture evolving trends. Longitudinal studies could offer more robust insights into how behavioral factors influence systematic risk over extended periods.

Thirdly, while our sample was carefully selected, it may not fully represent the diversity of the broader investor population, potentially limiting the generalizability of our results. Future research should aim to include more diverse samples across different demographic groups, investment experience levels, and cultural backgrounds.

Fourthly, our study focused on a specific geographical and cultural context, which may influence the applicability of our findings to global markets. Cross-cultural studies examining how behavioral factors vary across different national and cultural contexts could provide valuable comparative insights.

Lastly, our methodology did not include neuroscientific or physiological measurements, which could have provided additional insights into the cognitive and emotional processes underlying investor behavior. Future studies could benefit from integrating such methods to gain a more comprehensive understanding of the neural underpinnings of investment decisions.

Based on these limitations, we propose several directions for future research:

- Conduct longitudinal studies to examine how behavioral factors influence systematic risk over time, capturing potential changes in investor behavior across different market conditions.
- Integrate neuroscientific methods, such as fMRI or EEG, to explore the neural correlates of investment decision-making and their relationship to systematic risk.
- Expand the research to include a more diverse, global sample to enhance the generalizability of findings and explore potential cultural variations in investor behavior.
- Develop and validate more objective measures of investor behavior, possibly through experimental designs or analysis of real-world investment data.

- Investigate the potential moderating effects of factors such as financial literacy, investment experience, or access to information on the relationship between behavioral factors and systematic risk.
- Explore the impact of emerging technologies, such as robo-advisors or blockchain, on investor behavior and their implications for systematic risk.
- Examine how regulatory environments and policy interventions interact with behavioral factors to influence systematic risk.

By addressing these limitations and pursuing these future research directions, we can continue to deepen our understanding of the complex interplay between investor behavior and systematic risk, ultimately contributing to more effective risk management strategies and policy formulations in the financial sector.

Reference

Almeida, J., & Gonçalves, T. (2023). A systematic literature review of investor behavior in the cryptocurrency markets *Journal of Behavioral and Experimental Finance,* 37, 100785.Asemi, A., Asemi, A., & Ko, A. (2023). Adaptive neuro-fuzzy inference system for customizing investment type based on the potential investors' demographics and feedback. *Journal of Big Data*, 10, 87. https://doi.org/10.1186/s40537-023-00784-7

Asiabi-Aghdam, L., Rahimzadeh, A., Falahi, N., & Rajai, Y. (2021). Portfolio Selection based on Behavioral Economics (Case Study: Tehran Stock Market). *Journal of Financial Economics*, 15(55), 155-190. (In Persian)

Back, C., Morana, S., & Spann, M. (2023). When do robo-advisors make us better investors? The impact of social design elements on investor behavior. *Journal of Behavioral and Experimental Economics*, *103*, 101984.

Baker, H.K., Kumar, S., Goyal, N., & Gaur, V. (2019). How financial literacy and demographic variables relate to behavioral biases. *Managerial Finance*, 45(1), 124-146. https://doi.org/10.1108/MF-01-2018-0003

Battistini, N., Pagano, M., & Simonelli, S. (2014). Systemic risk, sovereign yields and bank exposures in the euro crisis. *Economic Policy*, 29(78), 203–251, https://doi.org/10.1111/1468-0327.12029

Chaudhry, S., & Kulkarni, C. (2021). *Design Patterns of Investing Apps and Their Effects on Investing Behaviors*. DIS '21: Proceedings of the 2021 ACM Designing Interactive Systems Conference, 777–788. https://doi.org/10.1145/3461778.3462008

Cherono, I., Olweny, T., & Nasieku, T. (2019). Investor behavior biases and stock market reaction in Kenya. *Journal of Applied Finance & Banking*, 9(1), 147-180.

Dadres, K., Tolouei Eshlaghi, A., & Radfar, R. (2018). The Role of Behavioral Finance in Perception of Individual Investors' Behavior (A Review of Empirical Evidence from Tehran Stock Exchange). *Knowledge of Investment*, 7(28) 83-102. (In Persian)

Derbali, A., & Hallara, S. (2016). Systemic risk of European financial institutions: Estimation and ranking by the Marginal Expected Shortfall. *Research in International Business and Finance,* 37, 113-134.

Faridniya, A., & Faridnia, M. (2019). Providing a model for allocating resources and choosing investment type using Data Envelopment Analysis (DEA) (Case Study: Social Security Organization). *Journal of Advanced Pharmacy Education & Research*, 9(S2), 112–24.

Fiordelisi, F., Galloppo, G., & Paimanova, V. (2024). Climate Change Fear: Natural Disasters and Investor Behavior. *Review of Corporate Finance*, *4*(1–2), 17-45.

Ghayour Baghbani, M., & Behboudi, O. (2017). Factors affecting the expression of investors' behavior with phenomenological approach. *Asset Management and Financing*, 5(3), 81, 57-76. (In Persian)

Gheisari, R., Salehi, S., & Ghobadi, S., (2021). The role of investors' fiscal knowledge on financial behavior in the capital market of Iran. *Journal of Financial Economics*, 15(54), 325-353. (In Persian)

Gurbaxani, A., & Gupte, R. (2021). A study on the impact of COVID- 19 on investor behaviour of individuals in a small town in the state of Madhya Pradesh, India. *Australasian Accounting, Business and Finance Journal*, 15(1), 70-92. doi:10.14453/aabfj.v15i1.6

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., and Tatham, R. L. (2006). *Multivariate Data Analysis*, 6th ed., Pearson Education, NJ.

Han, B., Hirshleifer, D., & Walden, J. (2022). Social transmission bias and investor behavior. *Journal of Financial and Quantitative Analysis*, *57*(1), 390-412.

Harrison, G. W., & Swarthout, J. T. (2023). Cumulative prospect theory in the laboratory: A reconsideration. In *Models of risk preferences: Descriptive and normative challenges* (pp. 107-192). Emerald Publishing Limited.

Hernández, E., Sittón, I., Rodríguez, S., Gil, A.B., García, R.J. (2019). *An Investment Recommender Multi-Agent System in*

Financial Technology. In: Graña M, López-Guede JM, Etxaniz O, Herrero Á, Sáez JA, Quintián H, Corchado E, editors. International Joint Conference SOCO'18-CISIS'18-ICEUTE'18. Cham: Springer International Publishing.

Isidore R., & Christie, P. (2019). The relationship between the income and behavioural biases. *Journal of Economics, Finance and Administrative Science*, 24(47), 127-144. https://doi.org/10.1108/JEFAS-10-2018-0111

Jafari, S., Garkez, M., Saeedi, P., & Moatoofi, A. (2020). The role of psychological and functional factors on willingness to invest in the stock market with the mediating role of investor satisfaction and perceived risk of investors. *Securities Analysis Financial Knowledge*, 13(48), 47-62. (In Persian)

Kari, M. (2016). Rational choice theory: An overview. *International Journal of Political Science*, 6(12), 75 -83.

Kengatharan, L., & Kengatharan, N. (2014). The influence of behavioral factors in making investment decisions and performance: Study on investors of Colombo Stock Exchange, Sri Lanka. *Asian Journal of Finance & Accounting*, 6(1).

Kent, D., & Hirshleifer, D. (2015). Overconfident investors, predictable returns, and excessive trading. *Journal of Economic Perspectives*, 29 (4), 61-88.

Khawaja, M.J., & Alharbi, Z.N. (2021). Factors influencing investor behavior: an empirical study of Saudi stock market. *International Journal of Social Economics*, 48(4), 587-601. https://doi.org/10.1108/IJSE-07-2020-0496

Kiruba, A.S., & Vasantha, V. (2021). Determinants in investment behaviour during the COVID-19 pandemic. *The Indonesian Capital Market Review*, 13(2), 1. DOI: 10.21002/icmr.v13i2.13351

Kostopoulos, D., Meyer, S., & Uhr, C. (2022). Ambiguity about volatility and investor behavior. *Journal of Financial Economics*, *145*(1), 277-296

Kovács, T., Ko, A., & Asemi, A. (2021). Exploration of the investment patterns of potential retail banking customers using two-stage cluster analysis. *Journal of Big Data*, 8(1), 141. https://doi.org/10.1186/s40537-021-00529-4.

Kumar, S., & Goyal, N. (2015). Behavioural biases in investment decision making – a systematic literature review. *Qualitative Research in Financial Markets*, 7(1), 88-108. https://doi.org/10.1108/QRFM-07-2014-0022

Kumar, S., & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. *Qualitative Research in Financial Markets*, 8(4), 270-287. https://doi.org/10.1108/QRFM-05-2016-0016

Lieder, F., Griffiths, T., Huys, Q., & Goodman, N. (2017). The anchoring bias reflects rational use of cognitive resources. *Psychonomic Bulletin & Review*. 25. 10.3758/s13423-017-1286-8.

Liu, H., & Chiu, Y. (2015). Sales framing, mental accounting, and discount assignments. *Asia Pacific Management Review*. 9. 10.1016/j.apmrv.2015.01.002.

Lukomnik, J., & Hawley, J. P. (2021). *Moving beyond modern portfolio theory: Investing that matters*. Routledge.

Manocha, S., Bhullar, P.S. & Sachdeva, T. (2023). Factors determining the investment behaviour of farmers – the moderating role of socioeconomic demographics. *Journal of Indian Business Research*, 15(3), 301-317. https://doi.org/10.1108/JIBR-02-2022-0045

Mensi, W., Hammoudeh, S., Shahzad, S.J., & Shahbaz, M. (2017). Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance*, 75, 258-279.

Mestre, R.A. (2021). Wavelet approach of investing behaviors and their effects on risk exposures. *Financial Innovation*, 7, 24. https://doi.org/10.1186/s40854-021-00239-z

Metawa, N., Hassan, M.K., Metawa, S., & Safa, M.F. (2019). Impact of behavioral factors on investors' financial decisions: case of the Egyptian stock market. *International Journal of Islamic and Middle Eastern Finance and Management*, 12(1), 30-

55. https://doi.org/10.1108/IMEFM-12-2017-0333

Nemati, M., & Rahmani Noroozabad, S. (2023). The role of psychological biases on investors' financial satisfaction: Evidence from investors in Tehran Stock Exchange. *Financial Economics*, 17(63), 1-24. (In Persian)

Ngoc, L. (2014). Behavior pattern of individual investors in stock market. *International Journal of Business and Management*, 9(1).

Phan, T. N. T., Bertrand, P., Phan, H. H., & Vo, X. V. (2023). The role of investor behavior in emerging stock markets: Evidence from Vietnam. *The Quarterly Review of Economics and Finance*, *87*, 367-376.

Pilatin, A., & Dilek, Ö. (2024). Investor intention, investor behavior and crypto assets in the framework of decomposed theory of planned behavior. *Current Psychology*, *43*(2), 1309-1324.

Purwidianti, W., Rahmawati, I. Y., & Dwiyanti, R. (2023). Overconfidence and herding bias on investment decisions the role of risk perception as a mediator. *Asian Journal of Economics, Business and Accounting*, *23*(18), 36-45.

Rahimpour Khanghah, F., Fazlzadeh, A.R., Naghdi, S., & Ahmadian, V. (2021). The effect of self-control and fiscal knowledge on financial satisfaction of investors in Tehran Stock Exchange with the mediating role of financial behavior. *Prospects for Financial Management*, 35, 173-197. (In Persian)

Rajasekar, A., Pillai, A.R., Elangovan, R. et al. (2023). Risk capacity and investment priority as moderators in the relationship between big-five personality factors and investment behavior: a conditional moderated moderated-mediation model. *Quality & Quantity*, 57, 2091–2123. https://doi.org/10.1007/s11135-022-01429-2

Renn, O., Laubichler, M., Lucas, K., Kröger, W., Schanze, J., Scholz, R. W., & Schweizer, P. J. (2022). Systemic risks from different perspectives. *Risk analysis*, *42*(9), 1902-1920.

Roodposhti Rahnama, F., & Zandieh, V. (2012). *Behavioral finance and neuro-finance (New financial paradigm) from theory to practice*, Islamic Azad University Press - Printing and Publishing Organization. (In Persian)

Rosyidah, U., & Pratikto, H. (2022). The role of behavioral bias on financial decision making: a systematic literature review and future research agenda. *Journal of Enterprise and Development (JED)*, 4(1), DOI: https://doi.org/10.20414/jed.v4i1.5102

Saadatzadeh Hesar, B., Abdi, R., Mohammadzadeh Salteh, H., & Narimani, M. (2022). The relationship between cognitive biases in investors' behavior-mediated by stock price fluctuations. *Journal of Financial Economics*, 15(65), 303-320. (In Persian)

Sandelowski, M., & Barroso, J. (2007). *Handbook for Synthesizing Qualitative Research*. New York: Springer Publishing Company.

Shahzad, S.J., Arreola-Hernandez, J., Bekiros, S., Shahbaz, & M., Kayani, G. (2018). A systemic risk analysis of Islamic equity markets using vine copula and delta CoVaR modeling. *Journal of International Financial Markets, Institutions and Money*, 56, 104-127.

Shaik, M. B. ., Kethan, M., Jaggaiah, T. & Khizerulla, M. (2022). Financial literacy and investment behaviour of IT professional in India. *East Asian Journal of Multidisciplinary Research*, 1(5), 777–788. https://doi.org/10.55927/eajmr.v1i5.514

Singh, R., Sarva, M., & Sharma, M. (2020). Investment behaviour and risktaking ability among retail investor: Role of demographic factors. *PalArch's Journal of Archaeology of Egypt / Egyptology*, 17(9), 5902 - 5926.

Smaga, P. (2014). *The Concept of Systemic Risk*. Systemic Risk Centre Special Paper No 5, The London School of Economics and Political Science, August 2014, Available at SSRN: https://ssrn.com/abstract=2477928

Tian, X., Ma, J., Li, L., Xu, Z., & Tang, M. (2022). Development of prospect theory in decision making with different types of fuzzy sets: A state-of-the-art literature review. *Information Sciences*, *615*, 504-528.

Wang, F., Zhang, R., Ahmed, F., & Muhammed, S. (2022). Impact of investment behaviour on financial markets during COVID-19: a case of UK. *Economic Research-Ekonomska*

Istraživanja, 35(1), 2273-2291, DOI:10.1080/1331677X.2021.1939089

Xi, D., O'Brien, T., & Irannezhad, E. (2020). Investigating the investment behaviors in cryptocurrency. *The Journal of Alternative Investments*, 23(2), 141-160. DOI: 10.3905/jai.2020.1.108

Yun, J. J., Ahn, H. J., Lee, D. S., Park, K. B., & Zhao, X. (2022). Inter-rationality; Modeling of bounded rationality in open innovation dynamics. *Technological Forecasting and Social Change*, *184*,

122015.Zahera, S.A. & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, 10(2), 210-251. https://doi.org/10.1108/QRFM-04-2017-0028

Zhang, Z., Sen, P., Wang, Z., Sun, R., Jiang, Z., & Su, J. (2024, March). FinBPM: A Framework for Portfolio Management-based Financial Investor Behavior Perception Model. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)* (pp. 246-257).

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