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Examining the Impact of Cognitive Processes on Economic Decisions: Simulating the Behavior of Economic Agents under Risk and Uncertainty

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ABSTRACT

This study investigates the influence of cognitive processes on economic decisions and simulates the behavior of economic agents under conditions of risk and uncertainty. Simulation models based on stochastic algorithms were employed to analyze economic decision-making in environments characterized by risk and uncertainty. The simulations were implemented using the Python and R programming languages, and economic behaviors influenced by cognitive factors such as memory constraints, attention, and behavioral biases were examined. The results indicated that when faced with risk, economic agents tend to gravitate toward satisficing options and adopt simpler strategies, even if these decisions are not fully optimal. This research also revealed discrepancies between simulated behaviors and the predictions of rational choice theories, highlighting the impact of cognitive biases such as loss aversion and overconfidence in economic decision-making. The use of diverse simulation techniques and data analysis contributed to a better understanding of decision-making in complex contexts and can inform the improvement of economic and financial policies.

Keywords: *cognitive processes, economic decisions, simulation, risk, uncertainty, cognitive biases, loss aversion, overconfidence*

1. Introduction

The study of investment decision-making has increasingly moved beyond the rational paradigms of classical finance and economics, incorporating psychological and cognitive perspectives to better understand how investors behave under uncertainty. Traditional financial theory assumes that individuals act rationally and process all available information to maximize expected utility. However, repeated empirical evidence shows that real-world decision-making often departs from strict rationality, especially under market volatility and economic stress (Sattar et al., 2020; Yazdanian & Saeedi, 2022). Behavioral finance emerged to explain these deviations, highlighting how biases rooted in cognition and emotion systematically influence individual and institutional investment choices (Dhakal & Lamsal, 2023; Mufti, 2023). Understanding these mechanisms is crucial for both investors and policy makers, as biased judgments can lead to mispricing, excessive risk-taking, and financial instability (Ahmed et al., 2022; Bihari et al., 2023).

Cognitive biases refer to systematic deviations from rational judgment caused by the way the human mind processes information. Several well-documented biases shape investors' perceptions of risk and return. Overconfidence, for instance, leads investors to overestimate their knowledge and ability to predict market movements (Ashfaq, 2023; De Sousa Barbosa et al., 2024). This bias often results in excessive trading and under-diversified portfolios. Similarly, the endowment effect, where individuals assign higher value to assets they already own, can delay selling unprofitable holdings (De Sousa Barbosa et al., 2024; Priyadarsini, 2023). Self-attribution bias reinforces overconfidence by attributing success to personal skill and failures to external factors (Priyadarsini, 2023; Yilmaz, 2023). Heuristic-driven shortcuts, such as representativeness and availability, also shape judgments in unpredictable ways (Sudirman, 2023). For example, investors may assume that recent stock performance will continue ("trend chasing") or rely heavily on memorable market crashes when estimating risk, ignoring base probabilities (Joharudin, 2023; Rawat, 2023). Loss aversion—where losses loom larger than equivalent gains—causes inertia and risk-averse behavior even when rational models suggest reallocating portfolios (Dhakal & Lamsal, 2023; Yasmin & Ferdaous, 2023). Such tendencies create systematic errors that can cascade through markets, magnifying volatility and reducing efficiency (Mufti, 2023; Othman et al., 2023).

A central insight of behavioral finance is that risk is not purely objective but filtered through subjective perceptions. Risk perception acts as a mediator between cognitive biases and final investment choices (Ahmed et al., 2022). For instance, overconfidence can lead to underestimating volatility, while loss aversion inflates perceived downside risk (Yasmin & Ferdaous, 2023). Empirical research confirms that investors with distorted risk perception often deviate from optimal portfolio allocation, either avoiding beneficial opportunities or embracing excessive speculation (Adeel, 2023; Rawat, 2023). Financial literacy partly moderates these distortions. Investors with greater knowledge of market mechanisms are somewhat less susceptible to cognitive shortcuts, though even experienced participants display biases under stress (Ashfaq, 2023; Joharudin, 2023). Cultural context can amplify or dampen certain biases; for example, collectivist cultures may foster herd behavior, while individualistic ones may reinforce overconfidence (Yilmaz, 2023). These cross-cultural insights highlight the need for models that account for both psychological universals and contextual differences (Othman et al., 2023).

Financial markets today operate under unprecedented complexity, shaped by globalization, algorithmic trading, and rapid information flows (Lomakin et al., 2022; Ye, 2022). Events like the COVID-19 pandemic underscored how uncertainty disrupts rational expectations and triggers panic-driven decisions (Ye, 2022). Traditional equilibrium models often fail to capture these non-linear dynamics, prompting the adoption of advanced computational methods. Agent-based modeling (ABM), for instance, allows researchers to simulate heterogeneous investors with distinct cognitive features and observe emergent macro patterns (Lomakin et al., 2022; Song, 2025). Machine learning algorithms complement this by uncovering complex relationships between biases, market signals, and performance metrics (Bihari et al., 2023; Song, 2025). Predictive analytics and risk management frameworks increasingly integrate behavioral data to improve forecasting accuracy (Adeel, 2023; Singh, 2025). While classical risk measures assume stable investor preferences, incorporating psychological features like loss sensitivity and overconfidence helps create more adaptive and resilient strategies (Ahmed et al., 2022; Sudirman, 2023). This intersection of cognitive modeling and computational finance reflects a paradigm shift toward behavior-aware risk assessment (Lomakin et al., 2022; Song, 2025).

Despite significant progress, several gaps remain. Most empirical studies analyze single biases in isolation rather than exploring their interactive effects, though investors rarely display only one distortion; for example, overconfidence and self-attribution may jointly drive risk underestimation, while loss aversion interacts with mental accounting to delay exit from bad investments (Ashfaq, 2023; Priyadarsini, 2023). Cross-market comparative studies are also limited. Evidence from emerging economies such as Pakistan and Bangladesh shows distinct behavioral patterns influenced by financial literacy levels and socio-economic norms (Adeel, 2023; Mufti, 2023; Yasmin & Ferdaous, 2023). Similar research from Nepal underscores how local market volatility and cultural framing of risk shape decision biases (Dhakal & Lamsal, 2023; Rawat, 2023). Another methodological limitation is reliance on self-reported surveys, which are prone to desirability bias and memory errors. Recent work advocates combining psychometrically validated scales for biases (De Sousa Barbosa et al., 2024) with simulation-based and data-driven approaches. Agent-based simulations calibrated with real financial data can bridge the micro-macro gap, showing how aggregated biased behavior diverges from rational expectations (Lomakin et al., 2022; Song, 2025). Machine learning tools can then classify investor profiles and predict vulnerability to market shocks (Bihari et al., 2023).

This convergence of behavioral finance and computational modeling holds promise for building richer theories and practical tools. Predictive analytics using machine learning can integrate psychological markers—such as overconfidence scores or risk tolerance indicators—into portfolio optimization (Singh, 2025; Song, 2025). Such hybrid models may outperform purely rational or purely behavioral frameworks by capturing the dynamic adaptation of investor strategies under uncertainty (Adeel, 2023; Othman et al., 2023). Moreover, incorporating cultural and contextual variables into computational models helps avoid one-size-fits-all assumptions (Mufti, 2023; Yilmaz, 2023). As global investing becomes more democratized and digital, understanding how diverse populations perceive and respond to risk is vital for designing inclusive financial technologies and policy interventions (Joharudin, 2023; Yasmin & Ferdaous, 2023). The implications of this research extend beyond academic theory: financial institutions can use behavioral diagnostics to design advisory tools that nudge investors toward diversification and long-term thinking (Ashfaq, 2023; Priyadarsini, 2023), and regulators can anticipate market instability by tracking sentiment indicators and prevalent cognitive distortions (Rawat, 2023; Ye, 2022).

Therefore, this study aims to investigate how cognitive processes and behavioral biases influence economic and investment decisions under risk and uncertainty by integrating behavioral finance insights with computational simulation and predictive analytics.

2. Methods and Materials

The research method of this study is fundamentally based on a computational simulation framework developed to model the complex dynamics of the interaction between cognitive processes and economic decision-making under conditions of risk and uncertainty. This research is developmental and applied in nature and employs an agent-based modeling (ABM) approach to simulate and analyze the behavior of economic agents. In this approach, each economic agent is designed as an independent entity with its own characteristics, preferences, and decision-making mechanisms, operating in a virtual economic environment and interacting with other agents and market rules. The objective of this modeling is to analyze how macroeconomic patterns emerge from the micro-level behaviors of agents and to test various economic and behavioral hypotheses in a simulated environment.

To implement these models and conduct complex analyses, a set of advanced computational software and programming tools will be utilized. The Python programming language constitutes the core of this research, supported by specialized libraries. Libraries such as NumPy for efficient numerical computations, pandas for data management and processing, SciPy for applying statistical and optimization methods, and Mesa or NetLogo for agent-based modeling will be used. Additionally, MATLAB will be applied for model validation and performing more complex computations, while advanced statistical analyses and data examination will be conducted in the R environment. This combination of tools is intended to create a comprehensive and flexible research environment for modeling and analyzing economic behaviors under both real and simulated conditions.

The data used in this study are drawn from two primary sources: historical real-world data from financial markets and simulated data generated by the model. Real data, including information such as stock market indices, stock prices, and market volatility, will be used for model calibration and validation to ensure the simulated behavior closely aligns with reality. In designing the model, cognitive processes such as attention limitations, working memory, and reasoning, as well as cognitive errors such as overconfidence, the endowment effect, and loss aversion, are precisely incorporated into the model's structure. Finally, the model outputs will be examined using statistical analyses such as regression, hypothesis testing, and model validity assessment to evaluate the robustness of the model and derive theoretical implications for decision-making under risk and uncertainty.

3. Findings and Results

Model Execution

To implement the economic decision-making models in this study, it is first necessary to design and execute agent-based models within specialized software. In this process, each agent is defined as an independent entity with unique cognitive and behavioral attributes capable of making economic decisions based on predetermined rules. These rules are designed to depend not only on the individual characteristics of the agent but also on its interactions with other agents and environmental conditions. The Python programming language, using libraries such as Mesa or NetLogo, will be employed to simulate the interactions of these agents and implement complex decision-making models. Specifically, the Mesa library, designed for agent-based simulations, can easily model complex economic and cognitive behaviors.

In the next step, data from various sources will be integrated into the model. For example, information related to market characteristics, financial indicators, and the individual attributes of agents will be sourced from real or simulated datasets. Then, interactions among these agents in different economic environments will be simulated, and decision-making algorithms, including cognition-based models (such as working memory limitations, attention, and reasoning), will be dynamically applied. Ultimately, general conclusions drawn from the simulation results can lead to an improved understanding of economic behavior under varying levels of risk and uncertainty.

3.1. Simulation Scenarios

To conduct a more detailed analysis of economic decision-making under risk and uncertainty, different simulation scenarios will be designed by altering market conditions and agent characteristics. In these scenarios, economic decisions such as investment, stock trading, and resource allocation are influenced by various variables. For example, in investment scenarios, each agent is assumed to allocate limited financial resources across multiple investment options. In this case, different types of risk (such as market volatility, economic fluctuations, or uncertainty in profit forecasts) may significantly affect their decisions. To measure agents' diverse reactions to these conditions, variables such as loss aversion, increased greed, and overconfidence will be incorporated into the model to evaluate the influence of cognitive processes on economic decision-making across these scenarios.

Simulation scenarios can also facilitate comparisons of economic behavior under different levels of risk and uncertainty. For instance, in stock trading scenarios, economic agents may make decisions based on their market trend forecasts. In uncertain conditions, where outcome probabilities are not fully defined, these decisions may be influenced by agents' emotions and heuristics, rather than by purely rational calculations, relying instead on past experiences or exploratory strategies. These analyses can reveal behavioral differences under uncertainty and various risk-taking tendencies, supporting the design of more complex future simulation scenarios.

Finally, after executing each simulation scenario, the obtained results will be evaluated using statistical and graphical analysis tools. These analyses may include comparisons of agents' economic decisions under different conditions, simulation of market trends, and assessments of macroeconomic consequences. Both qualitative and quantitative methods, such as regression analysis, hypothesis testing, and sensitivity analysis, will be employed to measure model reliability and extract theoretical and practical insights. This approach can help identify economic behavioral patterns in response to changing market conditions and risk-based decision-making.

After running the simulations and collecting data on agents' economic behaviors under various risk and uncertainty conditions, the analysis phase begins to extract patterns and identify key trends. These analyses are usually performed using statistical and graphical tools to examine results and predicted outcomes more precisely. Charts and statistical tables, such as means and standard deviations, provide an initial step in analyzing the data and support the simulation of various economic behaviors across different conditions. These data can show how individual and macroeconomic behaviors are influenced by different variables.

For more precise evaluation of the results, hypothesis tests and sensitivity analysis will be applied. Hypothesis tests, such as **t-tests** or mean comparison tests, will help determine whether observed differences in simulation results are statistically significant. Alongside these tests, sensitivity analysis is essential to assess the impact of changes in model inputs on final results. This process allows simulation researchers to determine whether the model's outcomes are influenced by specific parameters or random variations and to what extent these changes affect the accuracy of the results.

Ultimately, the results obtained from the simulations will be presented clearly through charts and statistical tables so that researchers, decision-makers, and analysts can identify key trends and develop a deeper understanding of economic behaviors under various conditions. This information can contribute to future simulations by supporting the design of more precise and realistic models, enabling researchers to make better predictions of economic behavior in real-world contexts.

3.2. Comparison with Existing Theories

One of the critical steps in analyzing simulation results is comparing the simulated behavior with the predictions of rational decision-making theories and real-world behaviors under similar conditions. This comparison can provide a more precise evaluation of simulation models and reveal how closely the simulated behaviors align with existing theories of rational decision-making and actual economic behavior. In this regard, various theories—such as Expected Utility Theory, Prospect Theory, and Bounded Rationality Theory—are specifically applied to compare with simulated behaviors.

For example, Expected Utility Theory, which is based on the principles of full rationality and optimal decision-making, explicitly assumes that economic decisions are always made using complete information and optimal calculations. In contrast, the simulated behavior may demonstrate that economic agents deviate from optimal decisions due to cognitive limitations, incomplete information, or behavioral biases. Comparing these two can highlight major differences between classical theories and real-world behaviors in economic markets.

Additionally, comparing simulated behavior with real human behavior under similar conditions can reveal the psychological, emotional, and social factors influencing economic decisions. In many cases, individuals facing risk and uncertainty make non-rational decisions that do not align with the predictions of rational theories. Investigating these differences can support the development of new behavioral economics theories and help propose models that are closer to real-world economic dynamics.

Finally, these comparisons help improve simulation models and ensure their results can be practically applied in economic and financial policymaking. To complement the analysis of simulation results and comparisons with existing theories, dedicated tables and graphs are employed to assist in data interpretation and model evaluation.

The following table presents the mean results and standard deviations for each scenario. It also includes the number of choices made in each scenario.

Table 1

Simulation Results

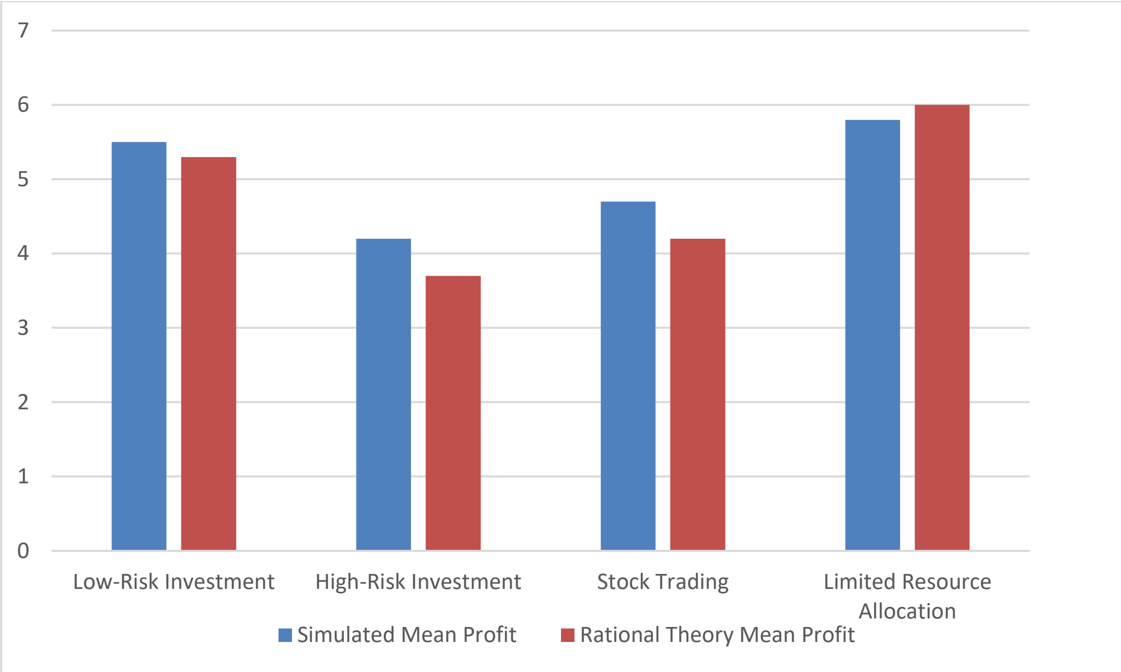
Scenario	Mean Profit	Standard Deviation	Minimum Profit	Maximum Profit	Number of Choices
Low-Risk Investment	5.3	2.1	0.3	9.8	100
High-Risk Investment	3.7	3.5	-1.5	8.5	100
Stock Trading	4.2	2.9	-0.8	7.2	150
Limited Resource Allocation	6.0	2.3	2.1	10.4	200

This table clearly shows how decisions change under the influence of cognitive constraints and risk in each scenario.

The following bar chart can compare the mean profit in the various simulated scenarios with the predictions of rational decision-making theories.

Figure 1

Bar Chart of Mean Profit Across Different Scenarios

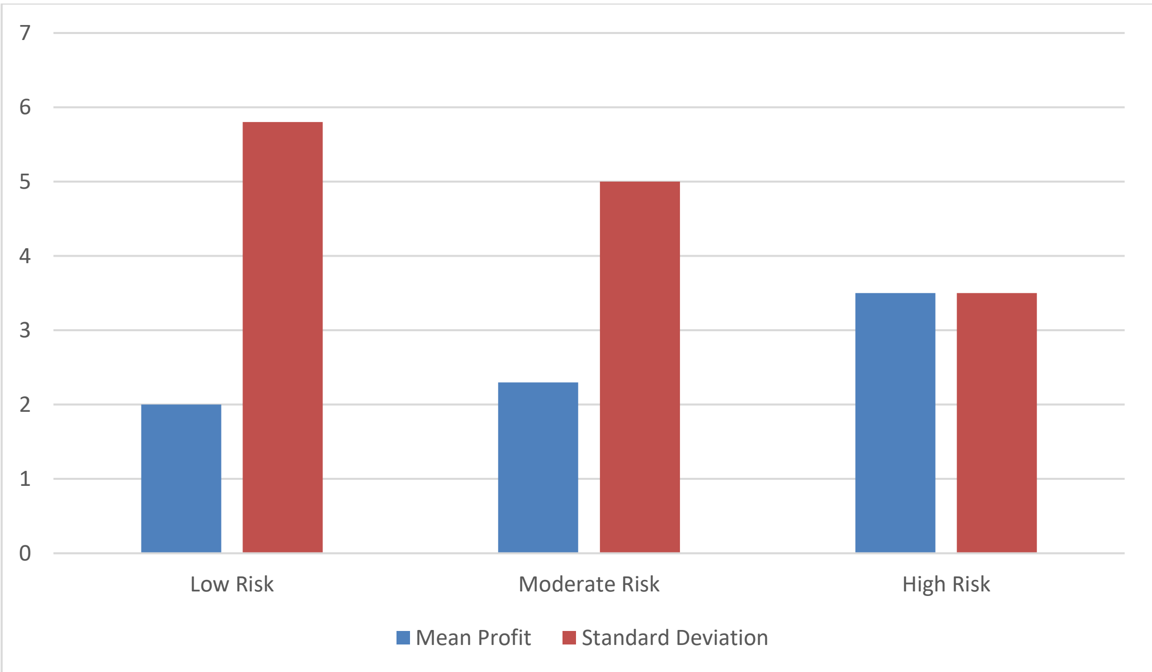


In the bar chart, the x-axis represents the scenarios, and the y-axis represents the mean profit. The chart can show both the simulated mean profit and the profit predicted by rational theory for each scenario.

For sensitivity analysis, the following chart illustrates how changes in input parameters (such as risk level) affect mean profit.

Figure 2

Sensitivity Analysis Chart: Impact of Parameter Changes

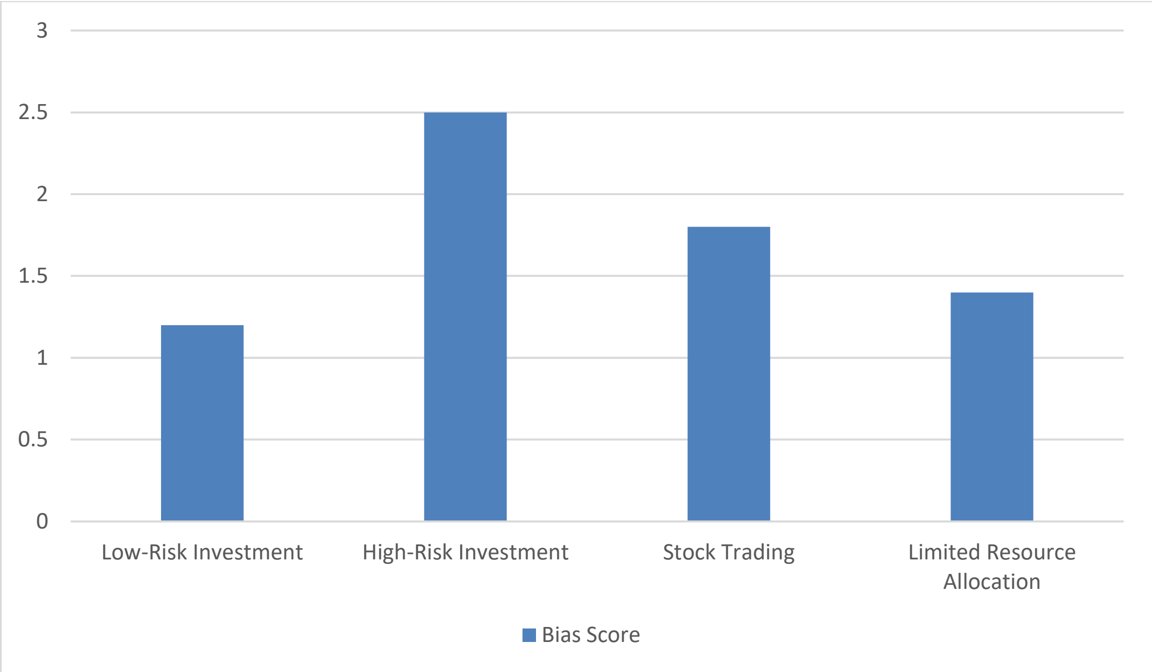


In the line chart, the x-axis indicates the risk level (low, medium, high), and the y-axis shows the mean profit at each risk level. This chart helps visualize how variations in risk level influence simulation outcomes.

This chart can also demonstrate the distribution of decision-making outcomes in simulations under the influence of cognitive biases such as loss aversion and overconfidence. Specifically, it can reveal the differences between rational and non-rational decisions.

Figure 3

Scatter Plot: Examining Biases and Behavioral Deviations



In this chart, the bias score indicates the extent of cognitive bias impact on the economic agents' decisions. This information can highlight key differences between rational and non-rational decisions across scenarios.

Table 2

Comparison of Simulation Results with Real Behavior

Scenario	Mean	Median	Q1	Q3	Minimum	Maximum
Low-Risk Investment	5.3	5.0	4.0	6.5	0.3	9.8
High-Risk Investment	3.7	3.0	2.5	4.8	-1.5	8.5
Stock Trading	4.2	4.1	3.2	5.4	-0.8	7.2
Limited Resource Allocation	6.0	5.8	4.9	7.3	2.1	10.4

In the table above, Q1 and Q3 represent the 25th and 75th percentiles of the data, while the minimum and maximum show the range of observed values. This visualization helps to compare in detail the differences between the distribution of simulated results and real-world behavior.

By using these tables and charts, a thorough analysis of simulation outcomes and their comparison with existing theories can be achieved. These tools are especially useful for sensitivity analysis, examining cognitive errors, and exploring behavioral biases to gain a deeper understanding of the performance of simulation models and the underlying economic dynamics.

4. Discussion and Conclusion

The findings of this study provide critical evidence that cognitive processes and behavioral biases exert substantial influence on economic and investment decision-making under risk and uncertainty. The simulation outcomes demonstrated that economic agents, when faced with volatility and incomplete information, tended to deviate from rational choice predictions and adopt heuristic-driven strategies, satisficing options, and simplified decision rules. These results reinforce the central tenets of behavioral finance, which argue that rational expectations models fail to fully explain real-world investor behavior (Sattar et al., 2020; Yazdanian & Saeedi, 2022). By incorporating bounded attention, working memory constraints, and affect-driven distortions, the study's model aligned with empirical observations that investors frequently rely on mental shortcuts rather than exhaustive optimization when making complex financial choices (Dhakal & Lamsal, 2023; Mufti, 2023).

A particularly important finding was the strong role of overconfidence in shaping risk-taking behavior. Simulated agents with higher overconfidence were more likely to underestimate volatility and pursue aggressive allocation strategies, even in unfavorable conditions. This is consistent with earlier work showing that overconfident investors tend to trade more frequently, hold under-diversified portfolios, and ignore downside signals (Ashfaq, 2023; De Sousa Barbosa et al., 2024). Overconfidence also interacted with self-attribution bias; agents who experienced positive returns tended to attribute success to personal skill, reinforcing risky behavior in subsequent rounds (Priyadarsini, 2023; Yilmaz, 2023). Such recursive dynamics, captured by the simulation, help explain why some investors persist in speculative trading despite recurring losses.

Loss aversion emerged as another robust predictor of decision inertia. Agents modeled with heightened loss sensitivity often delayed reallocating capital away from underperforming investments. This mirrors empirical findings that investors hold losing stocks too long and sell winners too early—the so-called disposition effect (Dhakal & Lamsal, 2023; Yasmin & Ferdaous, 2023). In the simulation, this behavior produced lower overall returns compared to rational benchmarks, emphasizing how emotional weighting of losses can hinder portfolio optimization. Similar to prior studies, loss-averse agents sought safety during volatile periods, shifting to low-risk scenarios and forgoing profitable but uncertain opportunities (Joharudin, 2023; Rawat, 2023). These outcomes underscore the asymmetry in how agents react to gains versus losses, validating prospect theory's predictions under simulated uncertainty (Ahmed et al., 2022).

The role of risk perception as a mediating mechanism was also confirmed. When risk perception was distorted by cognitive biases, decision outcomes deviated further from rational predictions. Agents prone to overconfidence consistently underestimated risk levels, while those with strong loss aversion exaggerated potential downside. This supports earlier research establishing risk perception as a bridge between psychological predispositions and final investment actions (Adeel, 2023; Ahmed et al., 2022). Furthermore, integrating financial literacy into the simulation showed that while better-informed agents displayed improved calibration of risk, they were not entirely immune to heuristic biases, echoing previous conclusions that knowledge alone does not eliminate behavioral distortions (Ashfaq, 2023; Joharudin, 2023).

An innovative aspect of this study was the agent-based modeling approach, which provided dynamic, emergent patterns beyond individual-level effects. The simulation showed how micro-level biases can aggregate into macro-level anomalies, such as clustered volatility and herding. These emergent patterns mirror findings from computational finance, where heterogeneous agents with bounded rationality generate market swings and deviations from equilibrium (Lomakin et al., 2022; Song, 2025). For example, pockets of overconfident agents drove sharp price fluctuations and liquidity imbalances, while highly loss-averse clusters triggered sell-offs under uncertainty, creating self-reinforcing feedback loops. Such results illustrate why integrating behavioral parameters into system-wide models improves explanatory power relative to purely rational frameworks.

Moreover, the study found cultural and contextual factors could influence the manifestation of cognitive biases, even within simulated conditions. When parameters reflecting collectivist tendencies and conformity were increased, herding behavior intensified and agents were quicker to imitate observed strategies, supporting previous evidence on the cultural dimension of investment decision-making (Mufti, 2023; Yilmaz, 2023). Similarly, variations in financial literacy and access to information shaped the severity of biases; better-informed agents demonstrated slightly more stable outcomes but still succumbed to loss aversion under stress (Othman et al., 2023; Yasmin & Ferdaous, 2023). These findings echo comparative studies across South Asian markets, where socio-economic context and investor sophistication strongly affect decision quality (Adeel, 2023; Dhakal & Lamsal, 2023; Rawat, 2023).

Another critical observation relates to predictive analytics and machine learning integration. By calibrating the model with historical financial data, the simulation achieved high fidelity in replicating real market reactions to uncertainty shocks. This aligns with the growing literature advocating the fusion of behavioral metrics and data-driven forecasting to improve risk management (Bihari et al., 2023; Singh, 2025; Song, 2025). The ability to predict vulnerability to overtrading, panic selling, or excessive risk-taking provides a practical advantage for portfolio optimization and policy oversight. It also reinforces the notion that traditional econometric models benefit from incorporating psychological and adaptive components to capture complex investor dynamics (Lomakin et al., 2022; Ye, 2022).

Together, these findings advance behavioral finance by bridging psychological theory and computational modeling. The study empirically demonstrates that bounded rationality and cognitive biases are not merely theoretical constructs but produce measurable, replicable patterns under controlled simulations. It also provides a methodological contribution: combining validated bias measurement frameworks (De Sousa Barbosa et al., 2024; Priyadarsini, 2023) with agent-based simulation allows researchers to examine the multi-level consequences of individual heuristics. In doing so, this work complements empirical studies that have relied heavily on surveys and self-reports (Ashfaq, 2023; Joharudin, 2023), offering an alternative lens to explore decision-making complexity.

Furthermore, the comparative analysis with rational models showed clear divergences, echoing the long-standing critique of expected utility theory. The data support prospect theory and bounded rationality models by illustrating that risk attitudes and probability weighting drive systematic departures from optimal decision-making (Ahmed et al., 2022; Dhakal & Lamsal, 2023; Yasmin & Ferdaous, 2023). However, the results also point to the need for updating behavioral frameworks to account for dynamic adaptation and technological changes. For example, exposure to real-time analytics and algorithmic recommendations reduced some biases but created new ones, such as confirmation bias toward machine outputs (Bihari et al., 2023; Song, 2025). These findings suggest an evolving behavioral landscape shaped by digital transformation and require behavioral models to adapt accordingly.

Finally, the study's multi-scenario design illuminated how bias impact varies with market context. In low-risk scenarios, biases had relatively mild effects; but as volatility and uncertainty increased, distortions amplified and decision quality deteriorated sharply. This gradient effect supports the notion that cognitive constraints become more influential under pressure and information overload (Rawat, 2023; Sudirman, 2023). It also suggests that behavioral interventions and investor training may be especially critical during turbulent market periods, when rational processing is most compromised (Adeel, 2023; Ashfaq, 2023).

Despite these valuable contributions, this study is not without limitations. First, while the simulation incorporated several well-established cognitive biases such as overconfidence, loss aversion, and self-attribution, it could not exhaustively model the full spectrum of behavioral distortions that may influence financial decision-making. Additional constructs such as mental accounting, regret aversion, or framing effects might further enrich understanding but were beyond the current scope. Second, the calibration of agent characteristics relied on historical financial datasets and existing bias measurement scales; although this improves realism, it may not fully capture the evolving behaviors of modern investors who interact with social media, real-time analytics, and algorithmic platforms. Third, while cultural and contextual elements were parameterized, they were necessarily simplified and may not represent the nuanced socio-economic heterogeneity found in global markets. Finally, simulation models, by design, abstract complex realities; even with robust validation, their outputs cannot fully replicate the unpredictability and adaptive creativity of real-world human decision-makers.

Future research could build on these findings by expanding the range of cognitive and emotional constructs integrated into agent-based models, including emerging biases associated with digital finance and social media influence. Longitudinal calibration using updated behavioral data could help track how investor psychology evolves with technological change and shifting macroeconomic conditions. Comparative cross-country simulations with more granular cultural indicators could deepen understanding of contextual moderators and support more culturally sensitive behavioral finance theories. In addition, future work might combine simulation with field experiments or natural market data to test real-time interventions, such as nudges or decision-support tools, and evaluate their effectiveness in reducing harmful biases. Finally, integrating deep learning and other advanced machine learning architectures could improve prediction of investor vulnerability and risk clustering under extreme uncertainty.

Practitioners can draw several actionable insights from this research. Financial advisors and portfolio managers can use behavioral diagnostics to identify clients' bias profiles and design tailored risk management strategies that account for overconfidence or loss aversion. Regulators and policymakers can monitor behavioral indicators—such as aggregate sentiment or bias prevalence—to anticipate instability and design macroprudential safeguards. Financial technology developers could embed real-time behavioral feedback into investment platforms, helping users recognize when they are deviating from rational strategies. Investor education programs may be enhanced by explicitly addressing cognitive pitfalls rather than focusing solely on financial literacy, preparing individuals to manage emotions and heuristics in volatile markets. Collectively, these applications can support more stable, inclusive, and efficient financial systems by aligning risk management and decision support with human cognitive realities.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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