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Impact of Artificial Intelligence on Behavioral Biases in Investment Decision-Making: A Gender-Based Study

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ABSTRACT: This research explores how AI affects behaviour biases when it comes to investing—particularly with respect to how investors’ gender influences their experience. A structured questionnaire was used to collect primary data from 100 participants. The study focuses on the following common types of behaviour biases that the sample showed evidence of: overconfidence; loss aversion; herd behaviour; regret avoidance; and being afraid of missing out (FOMO)—and it also assessed whether the use of AI-based investment tools assisted in decreasing these irrational patterns of behaviour. In general, most respondents reported that they were heavily using AI, particularly younger, educated males ($M = 4.23$ on a scale from 1 to 5). However, the study found no statistically significant evidence supporting AI’s ability to eliminate behavioural biases among its participants. There were significant differences associated with male/female usage: Men had a significantly higher degree of overconfidence than women ($M = 3.51$ vs. 2.59 , $p < 0.001$); and women had a significantly lower level of risk tolerance compared to men ($M = 3.74$ vs. 2.68 , $p < 0.001$). In addition, a positive correlation was found between AI tool usage and the quality of decision-making processes ($r = 0.287$). In conclusion, integrating AI with principles related to behaviour finance and employing gender-sensitive strategies will promote equitable and rational investment outcomes.

KEYWORDS: Artificial Intelligence, Behavioral Biases, Investment Decision-Making, Gender Differences, FinTech, Loss Aversion, Overconfidence

I. INTRODUCTION

For a long time, financial decision-making has been studied on the assumption that all investors behave in a rational manner. Classical financial models assume that investors evaluate risks and returns objectively and are attempting to maximize utility. However, the emergence of behavioral finance, as demonstrated by Kahneman and Tversky and others, has shown that actual investor behavior is often irrational and unreasoning; it is often affected by cognitive bias, emotional state and systematic psychological influences. Some of these biases—overconfidence, herding, loss aversion, regret and FOMO— have been thoroughly documented as sources of inefficient portfolio management, excessive trading activity and reduced investment returns. Moreover, research indicates that these biases do not affect all investors equally; rather, the effects of these biases are moderated by demographic factors, particularly gender. Overall, research has shown that male investors exhibit higher tendencies towards overconfidence and risk taker than do female investors, while female investors show a higher tendency towards risk aversion and are more conservative than their male counterparts.

II. REVIEW OF LITERATURE

The theoretical and empirical foundations of this study rest on an extensive body of literature spanning behavioral finance, gender studies in finance, and the emerging domain of FinTech adoption.

2.1 Behavioral Finance and Cognitive Biases: Kahneman and Tversky’s foundational Prospect Theory established that investors experience losses approximately twice as intensely as equivalent gains, generating persistent loss aversion. Pompian (2022) categorized behavioral biases into cognitive and emotional types, demonstrating their measurable negative impact on portfolio performance. Statman, Thorley, and Vorkink (2020) demonstrated that overconfident investors—predominantly male—trade significantly more frequently, resulting in lower net returns. Bikhchandani and Sharma (2021) documented how herding behavior causes investors to irrationally mimic crowd behavior, particularly



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during market volatility, rather than conducting independent analysis. Toma and Hancock (2022) further showed that social media-driven FOMO significantly influences retail investors—especially younger demographics—toward impulsive investment decisions.

2.2 Gender and Investment Behavior: Charness and Gneezy (2022) provided experimental evidence that women are significantly more risk-averse than men in financial decision-making contexts. Adil, Singh, and Ansari (2021) studied how behavioral biases affect men and women differently, finding that financial literacy moderates the relationship between bias and investment decision quality. Lusardi and Mitchell (2024) identified significant global gender gaps in financial literacy, with lower literacy linked to greater susceptibility to behavioral biases. Sugathan and Kumar (2024) investigated how gender influences investment decisions and found that AI can detect biases like overconfidence and risk aversion, helping investors make fairer decisions.

2.3 AI in Investment Decision-Making: Cao (2022) argued that AI-powered tools like robo-advisors reduce emotional and cognitive biases by processing data objectively. Brenner and Meyll (2022) found that robo-advisor users exhibit lower levels of loss aversion and herding behavior. Hendershott, Jones, and Menkveld (2021) showed that algorithmic trading systems improve market efficiency and reduce emotionally-driven errors. Venkatesh, Morris, and Davis (2023) applied TAM to explain that perceived usefulness and ease of use are primary drivers of technology adoption, with gender differences in AI acceptance also observed. Maheshwari and Samantaray (2025) further found that AI-led digital advisory services moderate Gen Z investors' biases including overconfidence and FOMO.

2.4 Research Gap: While prior research has independently examined behavioral biases, gender differences in investing, and AI adoption, remarkably few studies have integrated all three dimensions with empirical primary data. This study addresses that gap through structured survey-based quantitative analysis, combining behavioral finance, gender, and technology adoption into a unified framework.

III. THEORETICAL FRAMEWORK AND HYPOTHESES

This study is grounded in four complementary theoretical frameworks.

Behavioral Finance Theory posits that psychological biases—not pure rationality—drive financial decisions. Biases including overconfidence, herding, and FOMO are inherent to human cognition and systematically affect investor performance.

Prospect Theory (Kahneman and Tversky) explains asymmetric loss-gain evaluation: losses loom larger than equivalent gains, generating risk aversion and irrational holding of declining assets. Gender may moderate the degree of this loss sensitivity.

Technology Acceptance Model (TAM) suggests that perceived usefulness and ease of use determine technology adoption. Gender may moderate these perceptions in the context of AI investment tools, influencing how deeply each group integrates AI into their decision process.

Algorithmic Decision-Making Theory examines how AI can replace emotion-driven decisions with data-driven analysis, potentially reducing behavioral biases—though biased training data may also perpetuate or introduce new biases if platforms are not carefully designed.

Hypotheses

Based on these frameworks, three testable hypotheses were formulated:

H1: Behavioral biases have a significant impact on investment decision-making among investors.

H2: AI-based investment tools significantly influence and reduce behavioral biases in investment decision-making.

H3: There is a significant gender difference in the impact of AI-based investment tools on behavioral biases in investment decision-making.



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IV. RESEARCH METHODOLOGY

4.1 Research Design: This study employs a quantitative, descriptive-explanatory research design. A structured questionnaire with 25 closed-ended items on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was administered to 100 individual investors. The questionnaire was organized into four sections: (1) demographic characteristics; (2) AI tool usage; (3) behavioral biases covering overconfidence, herding, risk aversion, regret aversion, and FOMO; and (4) investment decision-making quality.

4.2 Sample Profile: Non-probability convenience sampling was used to recruit respondents familiar with or actively using AI-based investment platforms. The sample skewed young and educated: 52% were aged 21–30, 82% held graduate or postgraduate degrees, and 70% had three or fewer years of investment experience. Gender composition was 54% male, 44% female, and 2% other. The predominance of younger, digitally oriented respondents makes this sample particularly relevant for studying AI adoption behavior in investment contexts.

4.3 Statistical Techniques: Data were analyzed using Python (Google Colab) and Microsoft Excel. Statistical techniques employed included descriptive statistics (mean, standard deviation, frequency distributions), Pearson correlation analysis, multiple linear regression (H1), simple linear regression (H2), and independent samples t-tests (H3). Internal consistency was assessed via Cronbach's Alpha. The significance threshold was set at $\alpha = 0.05$ for all hypothesis tests.

4.4 Variable Operationalization: The independent variable is AI Tool Usage, measured by five Likert-scale items (Q1–Q5). The dependent variable is Investment Decision-Making quality (Q21–Q25). Five behavioral biases—overconfidence (Q6–Q8), herding (Q9–Q11), risk aversion (Q12–Q14), regret aversion (Q15–Q17), and FOMO (Q18–Q20)—serve as mediating/explanatory variables. Gender is operationalized as a nominal moderating variable.

V. DATA ANALYSIS AND FINDINGS

5.1 Descriptive Statistics:

Table 1 presents mean scores and standard deviations for all seven constructs across the 100-respondent sample.

Construct	N	Mean	Std. Dev.	Interpretation
AI Tool Usage	100	4.230	0.318	Very High Adoption
Overconfidence Bias	100	3.100	0.786	Moderate Presence
Herding Bias	100	3.073	0.651	Moderate Presence
Risk Aversion	100	3.127	0.886	Moderate Presence
Regret Aversion	100	3.180	0.672	Moderate Presence
FOMO	100	3.217	0.657	Moderate–High
Decision Making	100	3.844	0.392	High Quality

Scale: 1 = Strongly Disagree | 3 = Neutral | 5 = Strongly Agree



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The most prominent finding from descriptive analysis is the exceptionally high AI Tool Usage mean (4.23), reflecting the predominantly young, digitally native sample. Among behavioral biases, FOMO registers the highest mean (3.217), consistent with the influence of social media and peer comparisons on younger investors' impulsive investment tendencies. All five biases cluster in a narrow moderate range (3.07–3.22), indicating uniform but not extreme bias prevalence. Investment decision-making quality records a relatively high mean of 3.844, suggesting respondents perceive their decisions as largely rational—a perception that may itself reflect a degree of overconfidence.

5.2 Reliability Analysis: Cronbach's Alpha was calculated for each construct. AI Tool Usage achieved acceptable reliability ($\alpha = 0.612$) and Risk Aversion returned moderate reliability ($\alpha = 0.501$). Overconfidence returned low reliability ($\alpha = 0.259$). Herding ($\alpha = -0.012$), Regret Aversion ($\alpha = -0.009$), FOMO ($\alpha = -0.035$), and Decision Making ($\alpha = -0.087$) returned very low or negative alpha values, indicating that items within these constructs do not consistently measure a single underlying dimension. This is acknowledged as a methodological limitation; composite mean scores are used as the primary analytical basis, consistent with exploratory behavioral finance research.

5.3 Correlation Analysis:

Table 2 presents the Pearson correlation matrix for all seven constructs.

Variable	AI Usage	Overconfidence	Herding	Risk Aversion	FOMO	Decision Making
AI Usage	1.000	0.052	-0.027	-0.126	0.110	0.287
Overconfidence	0.052	1.000	-0.205	-0.407	-0.023	0.047
Herding	-0.027	-0.205	1.000	0.089	-0.132	0.093
Risk Aversion	-0.126	-0.407	0.089	1.000	0.136	0.032
FOMO	0.110	-0.023	-0.132	0.136	1.000	0.007
Decision Making	0.287	0.047	0.093	0.032	0.007	1.000

The most notable finding is the positive association between AI Tool Usage and Decision Making Quality ($r = 0.287$)—the strongest pairwise relationship in the entire matrix. A moderate negative correlation between overconfidence and risk aversion ($r = -0.407$) aligns with behavioral finance theory: highly overconfident investors perceive lower risk in the market, while risk-averse investors calibrate more conservatively. Most inter-bias correlations are weak (-0.13 to $+0.14$), confirming that the five biases operate as largely independent psychological constructs rather than a single unified dimension.



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VI. HYPOTHESIS TESTING

6.1 H1 — Impact of Behavioral Biases on Decision-Making:

Multiple regression was conducted with the five behavioral biases as predictors and investment decision-making quality as the dependent variable.

Predictor	B Coefficient	Std. Error	t-value	p-value
Intercept	3.414	0.391	8.733	<0.001***
Overconfidence	0.042	0.048	0.882	0.380 (ns)
Herding Bias	0.063	0.059	1.069	0.288 (ns)
Risk Aversion	0.019	0.043	0.435	0.664 (ns)
Regret Aversion	0.004	0.057	0.078	0.938 (ns)
FOMO	0.010	0.059	0.178	0.859 (ns)

Model Summary: $R^2 = 0.015$, $F = 0.288$, $p = 0.919$ | ns = not significant

The overall regression model is not statistically significant ($F = 0.288$, $p = 0.919$), with behavioral biases collectively explaining only 1.5% of variance in decision-making quality. No individual bias achieves significance (all $p > 0.05$). Consequently, H1 is not supported in this sample. The narrow clustering of bias means (3.07–3.22) reduces statistical variance, limiting regression sensitivity. A larger, more heterogeneous sample may yield stronger detectable effects.

6.2 H2 — Effect of AI on Behavioral Biases

Simple linear regression was conducted separately for each bias with AI Tool Usage as the predictor.

Dependent Variable	β Coefficient	R^2	p-value	Direction
Overconfidence Bias	+0.130	0.003	0.604	Increases (ns)
Herding Bias	-0.055	0.001	0.790	Reduces (ns)
Risk Aversion	-0.350	0.016	0.212	Reduces (ns)



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Regret Aversion	-0.007	0.000	0.973	Reduces (ns)
FOMO	+0.228	0.012	0.275	Increases (ns)

ns = not significant at $p < 0.05$, None of the five regression models achieve statistical significance, leading to non-rejection of the null hypothesis for H2. Notably, risk aversion shows the largest directional effect ($\beta = -0.350$), suggesting increased AI usage trends toward reduced risk aversion—a finding worth investigating in larger studies. Counterintuitively, AI usage shows positive associations with overconfidence ($\beta = +0.130$) and FOMO ($\beta = +0.228$), suggesting that greater market information exposure through AI channels may amplify opportunity awareness and confidence rather than tempering them—an important consideration for platform designers.

6.3 H3 — Gender Differences in Behavioral Biases:

Independent samples t-tests compared male ($n = 54$) and female ($n = 44$) investors across all seven constructs.

Construct	Male Mean	Female Mean	t-statistic	p-value	Decision
AI Tool Usage	4.244	4.200	0.684	0.495 (ns)	Accept H_0
Overconfidence Bias	3.506	2.591	6.913	<0.001***	Reject H_0
Herding Bias	2.988	3.212	-1.722	0.088 (ns)	Accept H_0
Risk Aversion	2.679	3.742	-7.586	<0.001***	Reject H_0
Regret Aversion	3.173	3.205	-0.229	0.819 (ns)	Accept H_0
FOMO	3.142	3.295	-1.149	0.253 (ns)	Accept H_0
Decision Making	3.856	3.823	0.408	0.684 (ns)	Accept H_0

Two highly significant gender differences emerge. First, male investors score significantly higher on overconfidence (3.51 vs. 2.59, $t = 6.913$, $p < 0.001$), confirming that male investors overestimate their ability to predict market outcomes, leading to excessive trading and under-diversification. Second, female investors score significantly higher on risk aversion (3.74 vs. 2.68, $t = -7.586$, $p < 0.001$), confirming that female investors are considerably more cautious—beneficial for avoiding large losses but potentially limiting long-term growth. Importantly, no significant gender differences exist in AI Tool Usage ($p = 0.495$) or Decision-Making Quality ($p = 0.684$), suggesting men and women are converging in their adoption of digital financial technology and their perceived investment outcomes.



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VII. DISCUSSION

The findings four major insights about the interplay, behavioral gender in contemporary investment decision-making.

AI adoption is widespread but does not automatically correct behavioral biases. The mean AI Tool Usage score of 4.23 demonstrates strong penetration of AI-based financial tools among younger, educated investors. However, the statistically insignificant regression results for both H1 and H2 reveal a critical distinction between tool access and behavioral change. Technology provides the analytical infrastructure; it does not override the psychological architecture of human decision-making. FinTech platforms must embed active de-biasing features—behavioral nudges, emotional alerts, decision pauses—rather than relying on passive data provision.

Gender differences in investment psychology are robust and consistent. The statistically significant findings for overconfidence (male-dominated) and risk aversion (female-dominated) reinforce decades of behavioral finance research and have direct practical implications. Financial advisors and AI platforms should implement gender-sensitive strategies—helping men recognize and moderate overconfidence, and helping women calibrate risk tolerance toward long-term growth goals.

AI positively correlates with perceived decision quality. The correlation $r = 0.287$ between AI Usage and Decision Making represents the strongest bivariate relationship in the entire correlation matrix. This suggests that AI serves as a supportive decision framework, helping investors organize information and reduce impulsive responses even without eliminating deep psychological biases. Future longitudinal research should track whether sustained AI engagement produces statistically significant bias reduction over extended periods.

FOMO and overconfidence may paradoxically increase with AI usage. The positive beta coefficients for AI usage predicting FOMO ($\beta = +0.228$) and overconfidence ($\beta = +0.130$) raise an important concern: greater information access through AI channels may amplify opportunity awareness and self-assurance rather than tempering them. This underscores the need for AI platforms to incorporate reflective design elements that slow impulsive decision-making and prompt critical self-evaluation before execution.

VIII. IMPLICATIONS

8.1 Theoretical Implications: This study extends Behavioral Finance Theory by empirically demonstrating that psychological biases persist even among technology-adopting, educated investors—confirming that knowledge and tool access alone cannot overcome cognitive and emotional tendencies. Prospect Theory is validated through the strong risk aversion findings, particularly among female investors, with gender emerging as a meaningful moderator of loss sensitivity. The Technology Acceptance Model is supported through high cross-gender AI adoption rates, while the finding that AI improves decision quality without eliminating biases refines algorithmic decision-making theory: AI enhances informational quality but does not replace psychological processing. Future theoretical models should integrate behavioral science into the architecture of financial technology design.

8.2 Managerial Implications: For FinTech companies and AI developers, the central lesson is that behavioral economics must be embedded in platform design. Real-time behavioral alerts, automated reminders when trading frequency exceeds personal benchmarks, and reflective decision prompts can help translate technological capability into genuine behavioral improvement. For financial advisors, the findings recommend gender-tailored behavioral coaching: strategies to moderate overconfidence in male clients and encourage calibrated risk-taking in female clients. Investment firms should also reconsider marketing strategies that exploit FOMO to attract younger investors, prioritizing long-term financial education and disciplined decision-making frameworks over short-term engagement metrics.

IX. LIMITATIONS AND SCOPE FOR FUTURE RESEARCH

This study is subject to several limitations. The sample of 100 respondents, though adequate for descriptive analysis, limits statistical power for regression and moderation analysis—contributing to non-significant results for H1 and H2. The convenience sampling methodology restricts geographic and demographic generalizability. Low Cronbach's Alpha



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values for several constructs indicate measurement limitations that future studies should address through validated psychometric scales. Future research directions include: (1) larger, geographically and demographically diverse samples enabling robust moderation and causation testing; (2) longitudinal designs tracking whether sustained AI engagement reduces biases over time; (3) inclusion of additional biases such as anchoring, confirmation bias, and mental accounting; (4) experimental or neurofinance methodologies capturing real-time cognitive and emotional responses to AI-driven recommendations; and (5) cross-cultural comparisons to assess whether patterns observed in this Indian sample are universal or context-specific. Platform-specific analyses of individual robo-advisors and trading applications would also yield more applicable insights for practitioners.

X. CONCLUSION

This study contributes empirical evidence to a growing but underexplored intersection of behavioral finance, gender studies, and FinTech. Examining 100 individual investors across behavioral, technological, and demographic dimensions, the research yields a nuanced portrait of modern investment behavior. Behavioral biases—including overconfidence, herding, risk aversion, regret aversion, and FOMO—are present at moderate levels among educated, technology-using investors. Despite exceptionally high adoption of AI investment tools, their usage does not statistically eliminate these biases. Instead, AI functions as a supportive analytical framework that correlates with higher perceived decision-making quality without directly addressing the underlying psychological mechanisms of bias generation.

Gender differences are the study's most statistically robust finding. Male investors exhibit significantly higher overconfidence and female investors significantly higher risk aversion—confirmed at $p < 0.001$. These findings align with established behavioral finance literature and underscore the continued relevance of gender as a moderating variable in investment behavior, even as men and women increasingly converge in their adoption of AI technologies and their perceived quality of investment decisions. The path forward for rational, equitable investing lies not in AI alone, but in the thoughtful integration of AI capabilities with behavioral awareness, gender-sensitive design, and financial literacy education. Human judgment—informed by psychological insight and supported by data-driven tools—remains indispensable in achieving optimal investment outcomes in an increasingly AI-mediated financial world.

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