



Exploring Gender Differences in Investment Decision-Making: The Role of AI in Identifying and Addressing Behavioral Biases

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Abstract

This study investigates how Gender effects investment decision-making and AI's potential to detect and reduce behavioral biases. We utilized a 5-point Likert scale to score demographics, investment decision-making, and behavioral bias identification in 354 people who completed a self-administered online survey. The study examined gender, investment choices, and AI's impact on Behavioral Biases using descriptive correlation and SEM. Men scored slightly higher in Investment Decision-Making than women. ($M = 3.7230$ vs. $M = 3.6784$). There is no statistical significance for this difference. ($t = 0.550$, $p = 0.583$). SEM indicates gender affects behavioral biases. ($\beta = 0.022$, $p < 0.05$) these biases were significantly good for investment performance ($\beta = 0.821$, $p < 0.05$). The findings reveal how gender and behavioral biases interact, suggesting AI could improve financial decision-making.

Keywords: Gender Differences, Investment Decision-Making, Behavioral Biases, Artificial Intelligence, Financial Decision-Making.

1. Introduction

Gender is playing a larger role in various sectors of society, such as finance and investment, influencing decision-making and economic performance. Traditional gender roles and preconceptions have led to inequalities in economic opportunity and decision-making. As the world strives for increased gender equality, Gender's impact on investing decisions and financial outcomes must be examined. Women take larger investment risks than men [1]. This could be due to a lack of confidence in their financial abilities, limited exposure to investment opportunities, or a preference for preserving their wealth over seeking higher profits. Furthermore, women face specific challenges in dismantling traditional gender stereotypes in the investment industry, seeking guidance on financial investments, and obtaining financial resources [2]. Policymakers, financial institutions, and researchers need to encourage gender diversity and inclusion in investment decision-making in order to narrow the financial literacy gap, enhance women's investment

opportunities, and assist women in entering the finance sector. Conventional economic theories suggest that individuals make wise financial choices by considering all the information and reasoning logically [3]. Research in neuroeconomics and behavioral finance demonstrates that individuals are prone to errors and biases. The prefrontal cortex and hippocampus communicate when making judgments thanks to neural connections. External factors and feelings can lead to bad decision-making. Financial advisers also exhibit biases when making decisions for clients regarding their finances. Personality traits and conduct regulation could enhance financial decision-making. Growing global worries surround artificial intelligence (AI), in specifically, behavioral economics and behavioral finance. Artificial intelligence (AI) can take over jobs that necessitate human intelligence [4]. It impacts the finance sector by offering personalized services, reducing costs, accelerating corporate expansion, and consistently tracking trends, data, and advancements. Financial



AI has accelerated knowledge-driven processes such as client investment plans and improved customer support for a more seamless experience. It is increasingly crucial in the realm of finance and trading transactions. Artificial intelligence has benefitted the economy and created fresh possibilities for financial professionals. AI and behavioral finance work well together. Investment decisions are influenced by various behavioral and psychological traits, some of which vary based on gender. Recent research shows differences in gender and the capability of AI to detect and eliminate biases in investment decisions, a topic traditionally overlooked by conventional financial theories. Financial institutions can offer personalized investment guidance through the utilization of artificial intelligence's data analysis and pattern recognition technology.

2. Literature review

[5] study from Shark Tank, men overestimated the value of companies by 57.19% and women by 50.50% when deciding on investments. This pointed to the existence of a gender gap that entrepreneurs and angel investors created for themselves. According to the research, encouraging more female company owners and angel investors to serve as role models is a way to support female entrepreneurship. Start-ups that show promise and have solid business ideas can also gain advantages by having diverse founder teams with both male and female members. [6] shows that in 2009, women accounted for around \$20 trillion in investments, which was equivalent to 27% of the world's wealth, demonstrating their growing influence in financial decision-making. While women investors show less enjoyment and confidence, men are more knowledgeable about different investment options, highlighting the increasing importance of women in investment decision-making. [7] employed a sequential mediation model to investigate the effect of biases in human behavior on the financial choices made by those who have life insurance. Involving 501 policyholders, the study found that biases greatly impact these decisions. The research enhanced behavioral finance by showing how disposition effects and overconfidence act as consecutive

mediators. The objectives included developing a more comprehensive model and enhancing understanding of improved investment strategies.

[8] investigated how biases in human behavior affect financial decision-making, with an emphasis on four common biases: overconfidence, framing, endowment, and loss aversion. Suggestions are provided for reducing these biases, such as collecting data from multiple sources, evaluating skills objectively, seeking advice from professionals, regularly monitoring portfolios, and visualizing potential outcomes in advance. [9] investigated how artificial intelligence (AI) is utilized, challenges faced, and possible advancements in the financial services sector. Language processing, artificial intelligence, and neural networks were some of the AI building blocks covered, as was the broad use of AI in financial institutions. In addition, the research highlighted how AI may improve decision-making, simplify operations, and reduce risks while also examining ethical and legal concerns. Moreover, it examined advanced technology such as explainable AI and deep learning. [10] looked into how Individuals' perceptions of risk are a key behavioral finance component that influences investing decisions in the Saudi stock markets. Research shows that blue chip bias, herding, and disposition effect all significantly affect how people perceive risk, but overconfidence solely affects investment decisions for the better. The research recommends investors to take into account their biases and create plans to reduce their influence, even though the results may not be relevant in different cultural settings. [11] increasing use of AI, particularly in generative AI models (GenAI), raised concerns about fairness and bias. These systems may maintain current inequalities by preserving generative biases that impact how individuals are represented in artificial data. Exploring different AI paradigms focusing on fairness and ethics, enhancing transparency, and collaborating across disciplines are mitigation tactics. [12] examined the growing prevalence of AI biases in autonomous decision-making systems with an emphasis on four primary areas: basic rights, people and communities, the banking industry, and companies and organizations.



For the benefit of automation engineers and practitioners all across the globe, researchers set out to identify and classify bias implications so that they might create focused solutions to mitigate risk.

3. Research Gap

The research identifies significant gaps in studies regarding gender and the impact of AI on reducing biases in making decisions about investments. Distinct gender biases in conduct in gender-diverse investing teams have been studied little. Few studies have examined how AI tools for different investor types reduce gender biases in investment environments. A variety of cultural contexts is needed to compare cultural influences on gender-based investing biases and actions as there is little research. There is little research on using ethical AI systems to reduce gender prejudice in financial decision-making. Different teams need to demonstrate their ability to remove behavioral biases in investment decisions in order to create a more equitable investing environment.

4. Aim and Objectives

4.1. Aim

This study aims to examine gender discrepancies in investing in great detail choices and the impact of artificial intelligence in detecting and mitigating cognitive biases, improving our comprehension of the way AI can impact financial choices.

4.2. Objectives

- The goal is to examine how gender affects investment decision-making.
- To identify specific behavioral biases that influence investment decisions across genders.
- Evaluate the impact of AI tools on reducing behavioral biases in investing decision-making.
- To look at how gender influences the correlation

between biases in behavior and financial outcomes.

4.3. Hypotheses

H1: When deciding to invest, there is a notable distinction-making styles between male and female investors.

H2: Male investors exhibit different behavioral biases compared to female investors, affecting their investment decisions.

H3: AI-driven tools significantly reduce behavioral biases in investment decisions for both genders.

H4: Gender moderates the correlation between unconscious prejudices and financial outcomes for women investors showing a greater improvement in performance when using AI tools.

5. Methodology

this research investigates how gender influences investment decision-making and how utilizing descriptive correlation analysis could help AI identify and mitigate behavioral biases (Figure 1). An online survey that individuals can complete themselves will collect demographic information, the Investment Decision-Making Scale, and a Behavioral Bias Identification Scale. The evaluations will employ a five-point Likert scale. A total of 354 individuals will participate in the survey. A study using Structural Equation Modelling will explore how gender, investing choices and the function of AI in mitigating prejudice are interrelated. The research aims to explore biased behaviours related to gender and how AI can enhance financial decision-making for different genders.

6. Result

H1: There is a significant difference in investment decision-making styles between male and female investors (Table 1).

Table 1 Group Statistics

Group Statistics					
	GENDER	N	Mean	Std. Deviation	Std. Error Mean
Investment_Decision _Making	Male	213	3.7230	.72690	.04981
	Female	171	3.6784	.86375	.06605

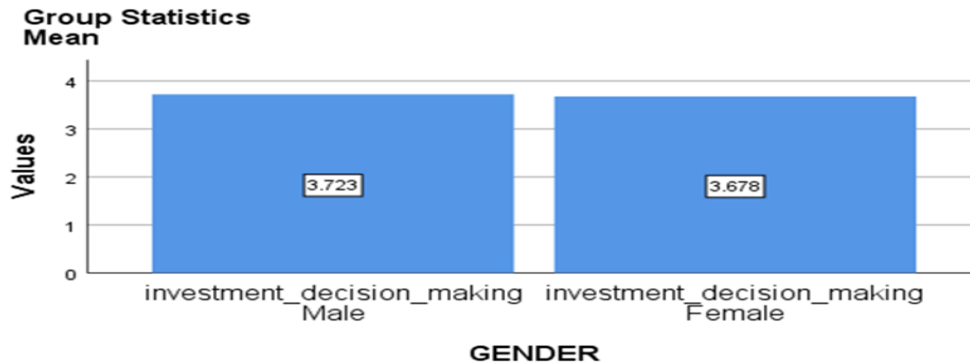


Figure 1 Group Statistics

The data in the table compare the ways in which men and women handle their money (Table 2). The data reveals that there were 213 males and 171 females in the sample. In comparison to women (M = 3.6784, SD = 0.86375), men score marginally higher (M = 3.7230, SD = 0.72690). There is more variation in

the responses from inside the female group (mean standard error = 0.06605) as compared to the male group (mean standard error = 0.04981). Generally speaking, the two sexes make comparable investing decisions, with men generally outperforming the females.

Table 2 Independent Samples Test

		Independent Samples Test						
		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Investment decision making	Equal variances not assumed	5.467	0.020	0.550	382	0.583	0.04464	0.08119

Using the test for independent samples, the table compares the investments of two groups. Results from the applicable Levene's Test for Variances contradict the hypothesis (F = 5.467, p = 0.020). We discover that the two groups' in a t-test when the p-value is bigger than 0.05 approaches to investing are comparable (t=0.550, df=382, p= 0.583). With a

standard error of 0.08119 and a mean difference of 0.04464, the effect size is tiny and does not meet statistical significance (Table 3 & 4).

H2: Male investors exhibit different behavioral biases compared to female investors, affecting their investment decisions.

Table 3 Group Statistics

	Gender	N	Mean	Std. Deviation	Std. Error Mean
Behavioral Biases	Male	213	3.7127	.72664	.04979
	Female	171	3.7135	.82604	.06317

The table (5) displays scores of behavioral biases for subjects, both male and female. The average score for men was 3.71 whereas women achieved a comparable score of 3.71, slightly elevated. The findings indicate that there are similar average biases

between genders, with slightly more variation in scores among females. Nevertheless, the level of score fluctuation is marginally higher within the male group.

Table 4 Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means				
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Behavioral Biases	Equal variances not assumed	4.138	0.043	-0.010	382	0.992	-0.00077	0.07931

The table displays Testing for behavioral biases using a t-test with independent samples and a variance equality check using Levene's test. A significance level of 0.043 and a level of F=4.138 were the results of Levene's test. shows that the variances are uneven (Figure 2). An analysis of variance in behavioral bias yields no significant

results (t-value = -0.010, p-value = 0.992, mean difference between groups = -0.00077, standard error = 0.07931). Consequently, women investors are more biased than men investors.

H3: AI-driven tools significantly reduce behavioral biases in investment decisions for both genders.

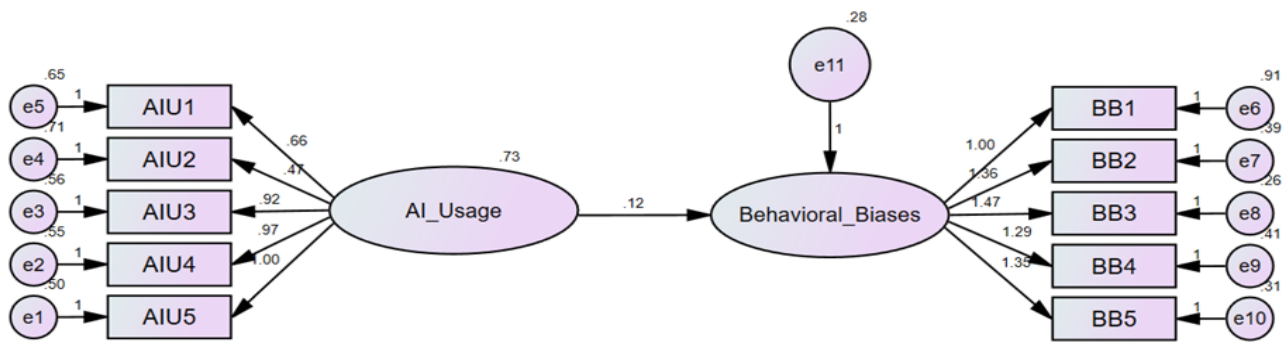


Figure 2 AI-Driven Tools

Table 5 Regression Weights

	Path	S.E.	Standardized estimates	C.R.	P
Behavioral Biases	<--- AI Usage	.040	.189	3.006	.003
AIU5	<--- AI Usage		.769		
AIU4	<--- AI Usage	.075	.746	12.921	***
AIU3	<--- AI Usage	.073	.723	12.635	***
AIU2	<--- AI Usage	.061	.432	7.683	***
AIU1	<--- AI Usage	.065	.570	10.123	***
BB1	<--- Behavioral Biases		.495		
BB2	<--- Behavioral Biases	.147	.765	9.296	***
BB3	<--- Behavioral Biases	.153	.841	9.626	***
BB4	<--- Behavioral Biases	.141	.736	9.139	***
BB5	<--- Behavioral Biases	.143	.796	9.444	***

A theoretical structural equation model links AI use to behavioral biases (Table 6). The model's independent factor is AI use and dependent factor is behavioral biases. The study found a strong correlation between behavioral biases and AI use ($\beta=.189, P<0.05$). AI use and behavioral biases are positively correlated with a 0.189 standard correlation coefficient. Strong correlation coefficients (C.R. values) imply statistical significance. All components have Since the p-values are greater than 0.05, the fit indices show that the model fits the data well. There was a positive correlation between AI Usage and Behavioral Biases, one of seven fit indices that evaluated the model's fitness (Figure 3). All of the correct metrics, including NFI, IFI, GFI, RFI, and CFI, were above 0.90, indicating a successful data fit ($\chi^2 = 50.508$). Similarly, both the RMR and RMSEA values are less than the critical value of 0.080. With RMSEA at 0.36, RMR at 0.34, GFI at 0.975, and CFI at 0.988, the model performed admirably in terms of fit (Table 7).

Table 6 Model Fit Summary

Variable	Values
Chi-square value(χ^2)	50.508
Degrees of freedom (df)	34
CMIN/DF	1.468
P value	0.034
GFI	0.975
RFI	0.951
NFI	0.963
IFI	0.988
CFI	0.988
RMR	0.34
RMSEA	0.36

H4: Gender moderates the relationship between behavioral biases and investment performance, with female investors showing a greater improvement in performance when using AI tools.

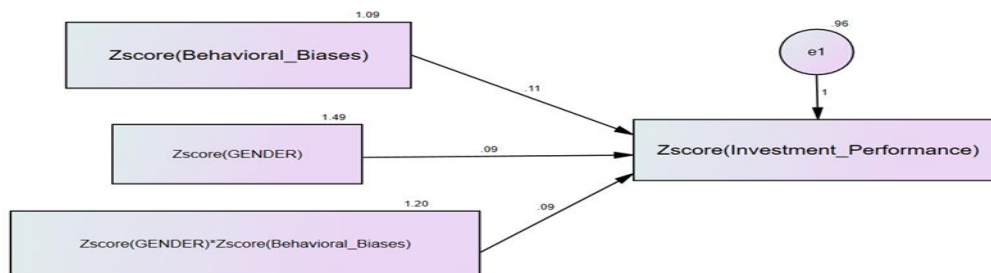


Figure 3 Behavioral Biases

Table 7 Regression Weights

Path	S.E.	Standardized estimates	C.R.	P
Z Investment Performance <--- Z Behavioral Biases	.048	.112	2.240	.025
Z Investment Performance <--- Z GENDER	.041	.110	2.182	.029
Z Investment Performance <--- Interaction 1	.046	.100	1.988	.047

The table (8) displays the Structural Equation Model (SEM) of Zscore (ZBehavioral Biases) and Zscore (ZInvestment Performance), with moderation by Zscore (ZGENDER). This comprehensive study examines all crucial pathways in the model,

incorporating measurement errors and evaluations. Zscore (ZInvestmentPerformance) and Zscore (ZBehavioral Biases) are strongly related, according to the path analysis hypothesis. This is supported by a Beta value of 0.821 and a significant

P-value less than 0.05. A significant and strong correlation was discovered between the Zscore of ZGENDER and the Zscore of ZBehavioral Biases ($\beta=0.022$, $P<0.05$).

7. Moderation Testing

In the evaluation of moderation, Zscore

(ZBehavioral Biases) is the independent variable, Zscore (ZInvestmentPerformance) is the dependent variable, and Zscore (ZGENDER) is the moderator. SPSS is utilized for generating interaction terms using standardized variable scores (Figure 4).

Table 8 Regression Weights

Path	S.E.	Standardized estimates	C.R	P
ZInvestmentPerformance <--- interaction1	.046	.100	1.988	.047

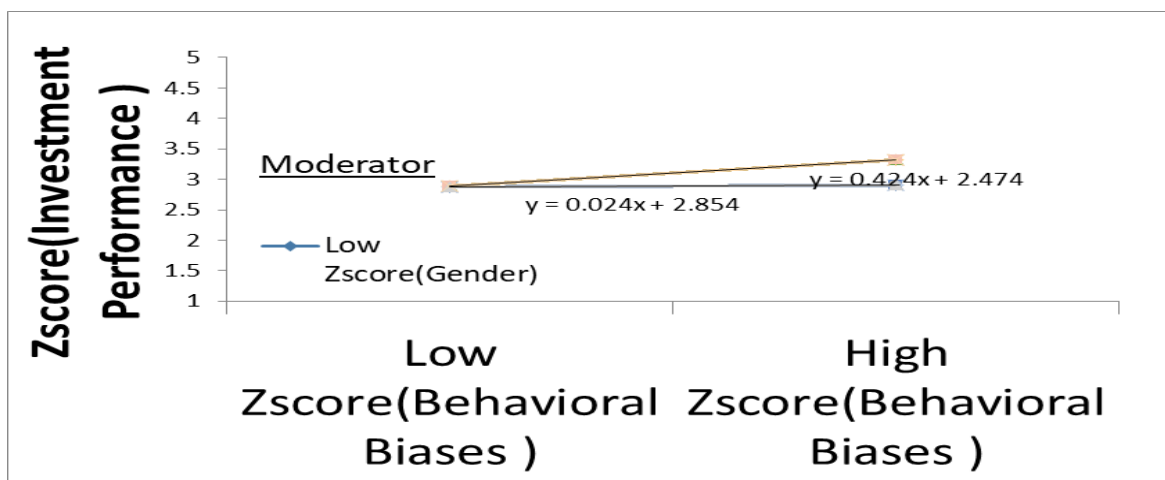


Figure 4 Z Investment Performance

Zscore (ZGENDER) was utilized for moderator testing. The combination of Z score (Z Behavioral Biases) and Zscore(ZEconomic_stability) has a substantial and favorable effect on Zscore (ZInvestmentPerformance) at a significance level lower than 0.05 and a beta coefficient of 0.100. We discovered statistical proof that Zscore(ZGENDER) influences our data.

Conclusion

The results of the study show that investing choices made by men and women are similar. The gender gap in scores is not statistically significant ($t=0.550$, $p=0.583$), while men do slightly better than women ($M = 3.7230$ vs. $M = 3.6784$). While there are noticeable changes in variances according to Levene's test, no differences in behavioral bias were found using as determined by the t-test for independent samples ($t = -0.010$, $p = 0.992$). According to SEM, behavioral biases are strongly associated with investment success ($\beta = 0.821$, $p <$

0.05) and there is a substantial gender effect on behavioral biases ($\beta = 0.022$, $p < 0.05$). The moderation study's conclusion that combining behavioral biases with economic stability improves investment performance ($\beta = 0.100$, $p < 0.05$) emphasizes the significance of gender as a moderator. These results suggest that gender and behavioral biases affect investment results, even while there is no bias in the investing operations it.

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