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Behavioural Biases and Investment Decision-Making: The Mediating Role of Risk Perception and Return Expectations

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Abstract:

Purpose: This study investigates how behavioral biases influence investment decision-making among millennial retail investors in emerging financial markets, focusing on the cognitive mechanisms of risk perception and return expectations.

Design/Methodology/Approach: A survey-based empirical analysis was conducted on millennial retail investors to examine herding behavior, loss aversion, overconfidence, and anchoring bias. A General Linear Model with bias-corrected bootstrapping was employed to test both direct and indirect effects of behavioral biases on investment decisions.

Findings: Herding and overconfidence exert direct, action-oriented effects on investment decisions. Loss aversion operates indirectly via risk perception and return expectations, highlighting perception-driven evaluation. Anchoring bias exhibits competitive mediation, negatively impacting decisions directly but positively influencing return expectations.

Originality/Value: This study contributes to behavioral finance literature by distinguishing perception-driven versus action-driven biases and elucidating the dual cognitive pathways through which behavioral biases influence millennial investors in emerging markets.

Research Limitations/Implications: The study relies on a survey of a limited sample, which may affect generalizability. Future research could explore larger samples or multiple emerging markets to validate and extend the findings.

Practical Implications: Findings provide actionable guidance for financial advisors, policymakers, and investor education programs, suggesting strategies to promote informed investment behavior among millennial retail investors.

Social Implications: Understanding behavioural biases and their cognitive mechanisms can enhance financial literacy and support more stable, informed participation in emerging financial markets.

Keywords: Behavioral finance, Investment decision-making, Behavioral biases, Risk perception, Return expectations, Millennial investors, Emerging Markets, Indian financial market, Overconfidence bias, Herding bias, Anchoring bias, Loss aversion.

1. Introduction

Traditional finance theory has long been dominated by the **Efficient Market Hypothesis (EMH)**, which assumes that financial markets are informationally efficient and that investors behave rationally. According to (FAMA, 1970), asset prices fully reflect all publicly and privately available information, implying that investors are unlikely to consistently achieve abnormal returns through irrational behavior or informational advantages. However, empirical observations of market anomalies, speculative bubbles, and financial crises have increasingly challenged these assumptions, paving the way for **Behavioral Finance** as an alternative theoretical perspective.

Behavioral finance integrates insights from psychology and economics to explain deviations from rational decision-making in financial markets. A foundational contribution is **Prospect Theory**, developed by (Kahneman & Tversky, 1991), which suggests that individuals evaluate gains and losses asymmetrically and rely on cognitive heuristics under uncertainty. Consequently, investors may exhibit **behavioral biases** such as herding behavior, loss aversion, anchoring bias, and overconfidence, which shape how they interpret financial information and make investment decisions.

Empirical research has demonstrated the significant role of psychological and demographic factors in shaping investor behavior. For example, (Hafez & Zhang, 2021,2025) identified the influence of herding and loss aversion on investment decisions in emerging markets, while (Ingale & Paluri, 2020) emphasized socio-economic determinants of investor behavior. (Calzadilla, 2020) highlighted the increasing importance of behavioral finance research among **retail investors**, rather than solely institutional participants. Despite these contributions, relatively few studies have examined the **combined effects of multiple behavioral biases** within a single analytical framework, particularly incorporating the cognitive mechanisms that mediate these effects.

While behavioral finance literature has expanded over the past decades (Bikas, 2013), **the mediating roles of risk perception and return expectations remain underexplored**, especially among millennial investors in emerging markets such as India. Millennials represent a distinct investor cohort characterized by high digital engagement, social connectivity, and participation in technology-driven trading platforms. These features may amplify the influence of behavioral biases on their investment decision-making processes.

In the Indian financial context, growing retail investor participation, rapid financial inclusion, and the proliferation of digital trading platforms have transformed investment behavior. However, **region-specific evidence on behavioral biases among millennial investors in major financial hubs like Bengaluru is limited**. Understanding how cognitive biases influence investment decisions via perceptions of risk and expected returns is crucial for developing effective financial education strategies and enhancing investor decision-making.

To address these gaps, the present study examines the combined influence of **overconfidence bias (OC), loss aversion (LA), anchoring bias (AB), and herding behavior (HB)** on investment decisions among millennial investors in Bengaluru. Importantly, the study proposes a **dual mediation framework** in which **risk perception** and **return expectations** act as cognitive channels linking behavioral biases to investment decisions. By integrating behavioral biases with perceptual evaluation processes, the study seeks to contribute to **behavioral finance theory** and provide practical insights for policymakers, financial advisors, and regulators aiming to promote more rational investment behavior among millennials. "This study contributes to behavioral finance literature by examining dual cognitive pathways through which multiple behavioral biases influence investment decisions, while providing actionable insights for policymakers and financial advisors targeting millennial investors."

Based on this framework, the study addresses the following research questions:

1. Which behavioral bias is most prevalent among millennial investors in Bengaluru?
2. What is the combined effect of overconfidence, loss aversion, herding behavior, and anchoring bias on investment decision-making?
3. Do risk perception and return expectations mediate the relationship between behavioral biases and investment decisions?

2. Review of literature

2.1 Psychological and Demographic Factors in Investment Decisions

Behavioral finance research emphasizes that psychological and demographic factors significantly influence investment decisions. For example, (Hafez & Zhang, 2021,2025) investigated representative bias, loss aversion, and herding among Egyptian investors, noting that investor behavior is context-dependent, particularly in post-pandemic markets. (Calzadilla, 2020) highlighted that while most studies focus on professional investors, understanding the decision-making of retail investors is critical for developing practical financial models. Demographic characteristics such as age, gender, investment experience, and personality traits also play a substantial role in shaping investment behavior (Dharmendra Singh, 2024). These findings underscore the importance of examining cognitive and demographic influences together when analyzing investment decisions.

2.2 Overconfidence Bias (OC) and Risk Propensity

Overconfidence bias reflects an investor's overestimation of knowledge or control over outcomes and often drives **risk-taking behavior**. (Syed Zain ul Abdin, 2022) noted that investors' illusion of control significantly affects their investment decisions, with cognitive biases generally increasing trading activity. (Zhang, 2025) highlighted that overconfidence manifests differently across investment stages, revealing a research gap regarding millennials, whose investment behavior is increasingly influenced by digital platforms and social networks. Foundational studies (Odena, 2001; Pradeep Kumar, 2024) demonstrate that overconfident investors tend to trade excessively, underestimate risks, and assume higher portfolio risk. Investigating the **mediating roles of risk perception and return expectations** helps explain how overconfidence translates into investment decisions, adding both theoretical depth and practical relevance.

2.3 Herding Bias (HB)

Herding behavior occurs when investors mimic the actions of others rather than relying on independent analysis. (Banerjee, 1992) and (Bikhchandani, 1992) theorized herding as a response to **informational cascades**. (Mitra, 2024) and (Aashna Sinha, 2022) found that internal and external factors, including social influence and market sentiment, drive herding, particularly in emerging markets. Herding can lead to irrational decisions during market bubbles and crashes and is closely linked to the fear of missing out (FOMO) phenomenon (Binu, 2024). Incorporating the **dual mediation framework**—risk perception and return expectations—offers a theoretical explanation for why herding biases influence investment choices differently among millennial investors, distinguishing **perception-driven from action-driven effects**.

2.4 Loss Aversion Bias (LA)

Loss aversion, a core concept of Prospect Theory (Kahneman & Tversky, 1991) describes investors' tendency to weigh potential losses more heavily than equivalent gains. (Zhou, 2023) reported that demographic factors, including age and gender, can amplify loss aversion, influencing investment behavior. (Siddhesh S. Soman, 2026) emphasized that recognizing loss aversion patterns can help financial advisors guide clients to mitigate risk-avoidant behavior. Post-COVID market shocks have intensified these tendencies, often resulting in panic-driven investment decisions (Ashraya.M, 2025). Examining **how risk perception and return expectations mediate the effect of loss aversion** adds novel insight into the cognitive mechanisms linking behavioral biases to investment decisions.

2.5 Anchoring Bias (AB)

Anchoring bias occurs when investors rely excessively on initial reference points, such as historical stock prices, leading to suboptimal investment decisions (Tversky, 1979) (Priya Kansal, 2015). Mitigation strategies include financial education, awareness programs, and decision-making tools (Wang, 2023) and (Zhong, 2025). Anchoring bias continues to affect portfolio management, stock valuation, and trading strategies (Zhong, 2025). Incorporating **dual mediation through risk perception and return expectations** provides a theoretical framework for understanding how anchoring shapes investment decisions beyond direct effects, contributing to behavioral finance theory and practical investor guidance.

2.6 Research Gaps

Based on the reviewed literature, the following gaps are identified:

1. Limited research examines the influence of **multiple behavioral biases** on investment decisions among millennials in Bengaluru.
2. Few studies investigate the **mediating roles of risk perception and return expectations** in linking behavioral biases to investment decisions.
3. There is a lack of empirical research assessing the **combined effects of overconfidence, herding, loss aversion, and anchoring biases** within a single analytical framework.
4. Most prior studies do not differentiate **perception-driven versus action-driven behavioral biases**, leaving both a theoretical and practical gap.

By addressing these gaps, the present study advances behavioral finance theory and provides actionable insights for **financial advisors, policymakers, and investor education initiatives** targeting millennials.

2.7 Hypotheses Development

Based on the literature and identified research gaps, the study proposes the following hypotheses:

Direct Effects:

- **H1:** Overconfidence bias (OC) positively influences investment decisions.
- **H2:** Herding bias (HB) positively influences investment decisions.
- **H3:** Loss aversion bias (LA) negatively influences investment decisions.
- **H4:** Anchoring bias (AB) negatively influences investment decisions.

Mediating Effects:

- **H5:** Risk perception mediates the relationship between behavioral biases (OC, HB, LA, AB) and investment decisions.
- **H6:** Return expectations mediate the relationship between behavioral biases (OC, HB, LA, AB) and investment decisions.

2.8 . Research Objectives

1. To examine the impact of behavioral biases (OC, LA, AB, HB) on investment decisions among millennial investors.
2. To assess the influence of behavioral biases (OC, LA, AB, HB) on **risk perception and return expectations** among millennials.
3. To analyze the **mediating effect of risk perception and return expectations** in the relationship between behavioral biases and investment decisions, differentiating perception-driven from action-driven biases.

3. Research methodology

The study adopts a **quantitative research design** to empirically investigate the influence of behavioral biases—overconfidence (OC), loss aversion (LA), anchoring (AB), and herding behavior (HB)—on investment decision-making among millennial investors in Bengaluru, India. The target population includes retail investors aged 29–44 (as of 2026) who actively participate in financial markets.

A **cross-sectional survey** approach was employed to collect primary data at a single point in time, which is efficient for analyzing relationships among behavioral biases, risk perception, return expectations, and investment decisions (Hafez & Zhang, 2021). **Purposive sampling** was used to select respondents with prior investment experience, ensuring the sample comprised knowledgeable participants. Out of 120 questionnaires distributed, **100 valid responses** were obtained, yielding a response rate of **83.33%**.

Data collection utilized a **structured questionnaire** divided into four sections:

1. Demographic information
2. Behavioral biases (OC, LA, AB, HB) (Aashna Sinha, 2022; Syed Zain ul Abdin, 2022; Bikas, 2013)
3. Risk perception and return expectations
4. Investment decision-making

All items were measured using a **5-point Likert scale** (1 = strongly disagree to 5 = strongly agree). A **pilot study** was conducted to ensure reliability and validity. **Cronbach's alpha values exceeded 0.70**, indicating strong internal consistency, and **exploratory factor analysis (EFA)** confirmed the construct validity of all scales.

For **statistical analysis**, SPSS was employed to conduct descriptive statistics, reliability tests, EFA, and hypothesis testing. A **General Linear Model (GLM) with bias-corrected bootstrapping** was used to estimate both direct and indirect relationships among constructs. The GLM mediation model was selected because it allows the simultaneous estimation of multiple predictors while accommodating **continuous dependent variables**. **Bootstrapping** was applied to obtain robust estimates and address potential violations of normality assumptions, enhancing the reliability of the mediation analysis.

This methodology enables a rigorous examination of **how perception-driven and action-driven behavioral biases influence investment decisions**, providing both theoretical insights and practical implications for policymakers, financial advisors, and investor education initiatives.

4. Results and discussion

4 .1 Results

Table 1:- Demographics frequency

Frequencies of Age			
Age	**Counts**	**% of Total**	**Cumulative %**
34-37	44	44.00%	44.00%
38-42	52	52.00%	96.00%
43-44	4	4.00%	100.00%
Frequencies of Gender			
Gender	**Counts**	**% of Total**	**Cumulative %**
Male	36	36.00%	36.00%
Female	64	64.00%	100.00%
Frequencies of Education Level			

Education Level	Counts	% of Total	Cumulative %
PUC	44	44.00%	44.00%
UG	24	24.00%	68.00%
PG	20	20.00%	88.00%
PROFESSIONAL	12	12.00%	100.00%
Frequencies of Occupation			
Occupation	**Counts**	**% of Total**	**Cumulative %**
Student	8	8.00%	8.00%
Private Employee	68	68.00%	76.00%
Public employee	4	4.00%	80.00%
Self employed	20	20.00%	100.00%
Frequencies of Monthly Income			
Monthly Income	**Counts**	**% of Total**	**Cumulative %**
20000-40000	40	40.00%	40.00%
40001-60000	56	56.00%	96.00%
60001 and above	4	4.00%	100.00%

The demographic profile shows that the majority of respondents are female (64%) and fall in the 38–42 age group (52%). Most have completed PUC education (44%) and are employed in the private sector (68%). Monthly income is predominantly in the Rs. 40,001–60,000 range (56%). This indicates a sample of predominantly mid-aged, educated, private-sector professionals with moderate income levels, which is relevant for understanding their investment behavior.

Table 2: Descriptive statistics:-

Descriptives													
	Age	**Gender**	**Education Level**	**Occupation**	**Monthly Income**	**Investment Experience**	**OC MEAN**	**HB MEAN**	**LA MEAN**	**AB MEAN**	**RISK MEAN**	**RETURN MEAN**	**ID MEAN**
N	100	100	100	100	100	100	100	100	100	100	100	100	100
Missing	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean	2.6	1.64	3	2.36	2.64	1.8	3.87	2.88	2.96	3.67	4.06	4.4	3.93
Median	3	2	3	2	3	2	4.33	1.67	1.67	4.33	4.5	4.5	4.6
Standard deviation	0.569	0.482	1.06	0.894	0.56	0.569	1.16	1.49	1.47	1.24	1.08	0.624	1.18
Minimum	2	1	2	1	2	1	1.33	1.33	1.33	1.33	1.5	1.5	1.4
Maximum	4	2	5	4	4	3	4.67	4.67	4.67	4.67	4.75	5	4.6

Skewness	0.269	-0.592	0.617	0.953	0.129	-3.16	-1.43	0.243	0.0933	-1.18	-1.87	-4.07	-1.5
Std. error skewness	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
Kurtosis	-0.792	-1.68	-0.946	-0.166	-0.764	-0.2	0.232	-1.93	-1.97	-0.483	1.65	17.1	0.37
Std. error kurtosis	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
Shapiro-Wilk W	0.723	0.607	0.809	0.692	0.72	0.736	0.63	0.703	0.723	0.655	0.514	0.396	0.574
Shapiro-Wilk p	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001

Descriptive analysis reveals that respondents exhibit high return expectations and optimism in investment decisions. Overconfidence bias has the highest mean among behavioral biases, suggesting a strong tendency toward self-assured decision-making. Risk perception is also elevated, indicating awareness of potential investment risks. Shapiro-Wilk test shows significant deviation from normality for all variables, and the extremely high kurtosis of return perception (17.1) highlights a pronounced expectation of high returns among the sample.

Table3:- Reliability test

Scale Reliability Statistics/Item Reliability Statistics			
	Cronbach's α	**Item-rest correlation**	**Cronbach's α**
OC1	0.926	0.88	0.88
OC2		0.797	0.952
OC3		0.9	0.853
HB1	0.963	0.945	0.933
HB2		0.889	0.971
HB3		0.938	0.934
LA1	0.962	0.952	0.932
LA2		0.892	0.965
LA3		0.94	0.937
AB1	0.939	0.912	0.888
AB2		0.8	0.987

AB3		0.938	0.865
RK1	0.933	0.865	0.906
RK2		0.806	0.925
RK3		0.851	0.911
RK4		0.854	0.91
RE1	0.844	0.751	0.771
RE2		0.585	0.84
RE3		0.738	0.777
RE4		0.687	0.807
ID1	0.965	0.954	0.954
ID2		0.962	0.962
ID3		0.953	0.953
ID4		0.962	0.962
ID5		0.954	0.954

Reliability analysis confirms that all constructs demonstrate strong internal consistency, with Cronbach's alpha values exceeding the acceptable threshold of 0.70. Overconfidence (α = .926), herding (α = .963), and loss aversion (α = .962) show particularly high reliability, indicating the measurement items for these biases are consistent. Investment decision shows excellent reliability (α = .965), validating the robustness of the survey instrument.

Table 4.1:- Exploratory factor analysis

Factor Loadings								
	Factor							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**Uniqueness**
OC1						0.813		0.1169
OC2						0.668		0.2794
OC3						0.899		0.0657
HB1			0.917					0.0374
HB2			0.853					0.1649
HB3			0.936					0.0825
LA1				0.927				0.0334
LA2				0.997				0.0502
LA3				0.883				0.0684
AB1					0.772			0.059
AB2					0.556			0.2813

AB3					0.783			0.0416
RK1		0.819						0.1788
RK2		0.926						0.199
RK3		0.782						0.1985
RK4		0.948						0.1533
RE1							0.56	0.2036
RE2							0.85	0.1179
RE3							0.68	0.1023
RE4							0.82	0.1611
ID1	0.95							0.0898
ID2	0.82							0.1929
ID3	0.98							0.0675
ID4	0.85							0.1635
ID5	0.92							0.0638

Note. 'Minimum residual' extraction method was used in combination with a 'oblimin' rotation

Table 4.2 Model Fit

Model Fit Measures							
	RMSEA 90% CI				**Model Test**		
RMSEA	**Lower**	**Upper**	**TLI**	**BIC**	**χ^2**	**df**	**p**
0.005	0.5	0.529	0.91	565	3984	146	<.001

Table 4.3 Assumption Checks

Bartlett's Test of Sphericity		
χ^2	**df**	**p**
6848	300	>.001

Exploratory factor analysis confirms a clean and valid factor structure. Factor loadings for each construct are strong, with no problematic cross-loadings. Investment decision, risk perception, herding, loss aversion, anchoring bias, overconfidence, and return perception all demonstrate acceptable loadings, supporting construct validity. Model fit indices (RMSEA = 0.005, TLI = 0.91) and Bartlett's test ($p < .001$) indicate that the factor model fits the data well, confirming appropriateness of the measurement scales.

Table5.1 General linear model

Model Info		
Info		
Model Type	Linear Model	OLS Model for continuous y
Model	lm	\`ID MEAN\` ~ 1 + \`OC MEAN\` + \`HB MEAN\` +

		\`LA MEAN\` + \`AB MEAN\`
Distribution	Gaussian	Normal distribution of residuals
Omnibus Tests	F	
Sample size	100	
Converged	yes	
Y transform	none	
C.I. method	Bootstrap BCa	5000 bootstrap samples
Note. All covariates are centered to the mean		

Table 5.2 Model Results

Model Fit					
R^2	**Adj. R^2**	**df**	**df (res)**	**F**	**p**
0.248	0.216	4	95	7.83	<.001

Table 5.3 ANOVA Omnibus tests

	SS	df	F	p	η^2p
Model	34.267	4	7.83	<.001	0.248
OC MEAN	7.615	1	6.961	0.01	0.068
HB MEAN	17.328	1	15.839	<.001	0.143
LA MEAN	6.017	1	5.499	0.021	0.055
AB MEAN	3.849	1	3.518	0.064	0.036
Residuals	103.934	95			
Total	138.202	99			

Table 5.4 Parametric Estimates coefficients

Parameter Estimates (Coefficients)									
				95% Confidence Intervals					
Names	**Effect**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	(Intercept)	3.928	0.105	3.717	4.13	0	95	37.554	<.001
OC MEAN	OC MEAN	0.309	0.117	0.054	0.562	0.302	95	2.638	0.01
HB MEAN	HB MEAN	0.322	0.081	0.181	0.479	0.406	95	3.98	<.001
LA MEAN	LA MEAN	0.19	0.081	0.033	0.34	0.237	95	2.345	0.021
AB MEAN	AB MEAN	-0.215	0.114	-0.407	-0.02	-0.225	95	-1.876	0.064

Table 5.5 Assumption Checks

Test for Homogeneity of Residual Variance			
Test	**Statistics**	**df1**	**p**
Breusch-Pagan Test	66.4	4	<.001

Test for Normality of residuals		
Test	**Statistics**	**p**
Kolmogorov-Smirnov	0.166	0.008
Shapiro-Wilk	0.896	<.001
Note. ties should not be present for the one-sample Kolmogorov-Smirnov test		
Collinearity statistics		
Term	**VIF**	**Tolerance**
OC MEAN	1.66	0.604
HB MEAN	1.31	0.761
LA MEAN	1.29	0.775
AB MEAN	1.82	0.55

The linear model shows that overconfidence, herding, and loss aversion significantly predict investment decisions among millennials in Bengaluru, while anchoring bias does not. The model explains 24.8% of the variance ($F = 7.83$, $p < .001$). Assumption checks reveal violations of normality and homoscedasticity, which were addressed using 5000 bootstrap samples, ensuring robust estimates. Multicollinearity is not a concern (VIF < 2).

6.1 General Linear Model

Model Info		
Info		
Model Type	Linear Model	OLS Model for continuous y
Model	lm	\`RISK MEAN\` ~ 1 + \`OC MEAN\` + \`HB MEAN\` + \`LA MEAN\` + \`AB MEAN\`
Distribution	Gaussian	Normal distribution of residuals
Omnibus Tests	F	
Sample size	100	
Converged	yes	
Y transform	none	
C.I. method	Bootstrap BCa	5000 bootstrap samples
SE method	Robust	.
Note. All covariates are centered to the mean		

6.2 Model Results

Model Fit					
R^2	**Adj. R^2**	**df**	**df (res)**	**F**	**p**
0.117	0.08	4	95	3.15	0.018

6.3 ANOVA OMNIBUS tests

ANOVA Omnibus tests					
	SS	**df**	**F**	**p**	**η^2p**
Model	13.412	4	3.147	0.018	0.117
OC MEAN	0	1	0	0.992	0
HB MEAN	1.758	1	1.346	0.249	0.017
LA MEAN	9.233	1	7.802	0.006	0.084
AB MEAN	0.509	1	0.702	0.404	0.005
Residuals	101.228	95			
Total	114.64	99			
Note. Inferential tests and p-values are based on robust estimation.					

6.4 Parameter Estimates

Parameter Estimates (Coefficients)								
			95% Confidence Intervals					
Names	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	4.06	0.106	3.849	4.254	0	95	38.432	<.001
OC MEAN	-0.001	0.106	-0.191	0.214	-0.001	95	-0.009	0.992
HB MEAN	0.102	0.088	-0.063	0.274	0.142	95	1.16	0.249
LA MEAN	0.236	0.084	0.075	0.391	0.322	95	2.793	0.006
AB MEAN	0.078	0.093	-0.105	0.258	0.09	95	0.838	0.404
Note. Inferential tests and p-values are based on robust estimation.								

6.5 Assumption checks

Test for Homogeneity of Residual Variance			
Test	**Statistics**	**df1**	**p**
Breusch-Pagan Test	16.2	4	0.003

Test for Normality of residuals		
Test	**Statistics**	**p**
Kolmogorov-Smirnov	0.253	<.001
Shapiro-Wilk	0.758	<.001
Note. ties should not be present for the one-sample Kolmogorov-Smirnov test		

Collinearity statistics		
Term	**VIF**	**Tolerance**
OC MEAN	1.66	0.604
HB MEAN	1.31	0.761
LA MEAN	1.29	0.775
AB MEAN	1.82	0.55

Bootstrapped robust regression indicates that only loss aversion significantly predicts risk perception (β = 0.236, p = .006), explaining 11.7% of the variance (p = .018). Overconfidence, herding, and anchoring bias do not significantly influence risk perception. These findings suggest that investors' cautiousness is primarily influenced by potential losses rather than other behavioral biases.

7.1 General Linear Model

Model Info		
Info		
Model Type	Linear Model	OLS Model for continuous y
Model	lm	\`RETURN MEAN\` ~ 1 + \`OC MEAN\` + \`HB MEAN\` + \`LA MEAN\` + \`AB MEAN\`
Distribution	Gaussian	Normal distribution of residuals
Omnibus Tests	F	
Sample size	100	
Converged	yes	
Y transform	none	
C.I. method	Bootstrap BCa	5000 bootstrap samples

SE method	Robust	
Note. All covariates are centered to the mean		

7.2 Model Results

Model Fit					
R^2	**Adj. R^2**	**df**	**df (res)**	**F**	**p**
0.266	0.235	4	95	8.6	<.001

7.3 Anova omnibus Test

ANOVA Omnibus tests					
	SS	**df**	**F**	**p**	**η^2p**
Model	10.237	4	8.602	<.001	0.266
OC MEAN	0.625	1	2.123	0.148	0.022
HB MEAN	0.041	1	0.27	0.604	0.001
LA MEAN	2.918	1	8.499	0.004	0.094
AB MEAN	2.27	1	5.349	0.023	0.074
Residuals	28.263	95			
Total	38.5	99			
Note. Inferential tests and p-values are based on robust estimation.					

7.4 Parameter Estimates.

Parameter Estimates (Coefficients)								
			95% Confidence Intervals					
Names	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	4.4	0.057	4.282	4.504	0	95	76.956	<.001
OC MEAN	0.088	0.061	-0.008	0.225	0.164	95	1.457	0.148
HB MEAN	0.016	0.03	-0.038	0.076	0.037	95	0.52	0.604
LA MEAN	0.133	0.045	0.046	0.215	0.313	95	2.915	0.004
AB MEAN	0.165	0.071	0.03	0.305	0.327	95	2.313	0.023
Note. Inferential tests and p-values are based on robust estimation.								

7.5. Assumption checks

Test for Homogeneity of Residual Variance			
Test	**Statistics**	**df1**	**p**
Breusch-Pagan Test	36.1	4	<.001

Test for Normality of residuals

Test	**Statistics**	**p**
Kolmogorov-Smirnov	0.212	<.001
Shapiro-Wilk	0.764	<.001
Note. ties should not be present for the one-sample Kolmogorov-Smirnov test		

Collinearity statistics		
Term	**VIF**	**Tollerance**
OC MEAN	1.66	0.604
HB MEAN	1.31	0.761
LA MEAN	1.29	0.775
AB MEAN	1.82	0.55

Regression results reveal that loss aversion (β = 0.133, p = .004) and anchoring bias (β = 0.165, p = .023) significantly predict return expectations, accounting for 26.6% of variance (p < .001). Overconfidence and herding bias do not significantly affect return perception, indicating that expectation of returns is more influenced by sensitivity to losses and reliance on reference points than by self-confidence or following others.

Table 8.1 :- GLM Mediation Model

Models Info		
Mediators Models	**m1**	**RETURN MEAN ~ OC MEAN + HB MEAN + LA MEAN + AB MEAN**
	m2	**RISK MEAN ~ OC MEAN + HB MEAN + LA MEAN + AB MEAN**
Full Model	**m3**	**ID MEAN ~ RETURN MEAN + RISK MEAN + OC MEAN + HB MEAN + LA MEAN + AB MEAN**
Indirect Effects	**IE 1**	**OC MEAN ⇒ RETURN MEAN ⇒ ID MEAN**
	IE 2	**OC MEAN ⇒ RISK MEAN ⇒ ID MEAN**
	IE 3	**HB MEAN ⇒ RETURN MEAN ⇒ ID MEAN**
	IE 4	**HB MEAN ⇒ RISK MEAN ⇒ ID MEAN**
	IE 5	**LA MEAN ⇒ RETURN MEAN ⇒ ID MEAN**
	IE 6	**LA MEAN ⇒ RISK MEAN ⇒ ID MEAN**

	IE 7	**AB MEAN ⇒ RETURN MEAN ⇒ ID MEAN**
	IE 8	**AB MEAN ⇒ RISK MEAN ⇒ ID MEAN**
Sample size	**N**	**100**

Table 8.2: - Mediation

Indirect and Total Effects								
				95% C.I. (a)				
Type	**Effect**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
Indirect	**OC MEAN ⇒ RETURN MEAN ⇒ ID MEAN**	0.08276	0.0589	0.00376	0.2431	0.08102	1.40616	0.16
	OC MEAN ⇒ RISK MEAN ⇒ ID MEAN	3.18E-04	0.0356	-0.0746	0.0613	3.12E-04	0.00894	0.993
	HB MEAN ⇒ RETURN MEAN ⇒ ID MEAN	0.01467	0.0386	-0.0279	0.0756	0.01853	0.38016	0.704
	HB MEAN ⇒ RISK MEAN ⇒ ID MEAN	-0.0324	0.0272	-0.118	0.0125	-0.04091	-1.1899	0.234
	LA MEAN ⇒ RETURN MEAN ⇒ ID MEAN	0.12411	0.0481	0.03736	0.228	0.15463	2.58023	0.01
	LA MEAN ⇒ RISK MEAN ⇒ ID MEAN	-0.07459	0.0366	-0.1645	-0.0194	-0.09293	-2.0406	0.041
	AB MEAN ⇒	0.15434	0.0651	0.02631	0.3293	0.16186	2.37117	0.018

	RETURN MEAN ⇒ ID MEAN							
	AB MEAN ⇒ RISK MEAN ⇒ ID MEAN	-0.02468	0.0359	-0.0956	0.0239	-0.02589	-0.6867	0.492
Component	**OC MEAN ⇒ RETURN MEAN**	0.08838	0.0594	0.00135	0.2484	0.16392	1.48678	0.137
	RETURN MEAN ⇒ ID MEAN	0.93646	0.2163	0.51011	1.2396	0.49427	4.32904	<.001
	OC MEAN ⇒ RISK MEAN	-0.00101	0.1125	-0.2005	0.2083	-0.00108	-0.0089	0.993
	RISK MEAN ⇒ ID MEAN	-0.31641	0.1143	-0.5208	-0.1308	-0.28818	-2.7681	0.006
	HB MEAN ⇒ RETURN MEAN	0.01567	0.0411	-0.0325	0.0839	0.03749	0.38163	0.703
	HB MEAN ⇒ RISK MEAN	0.10241	0.0777	-0.0708	0.2613	0.14198	1.31789	0.188
	LA MEAN ⇒ RETURN MEAN	0.13254	0.0412	0.04881	0.2216	0.31284	3.21339	0.001
	LA MEAN ⇒ RISK MEAN	0.23574	0.0781	0.07337	0.3967	0.32246	3.02009	0.003
	AB MEAN ⇒ RETURN MEAN	0.16481	0.0582	0.03486	0.3115	0.32747	2.83412	0.005
	AB MEAN ⇒ RISK	0.07801	0.1101	-0.0988	0.2647	0.08983	0.70886	0.478

	MEAN							
Direct	**OC MEAN ⇒ ID MEAN**	0.22547	0.1063	-0.0448	0.4843	0.22072	2.12083	0.034
	HB MEAN ⇒ ID MEAN	0.33923	0.0729	0.19505	0.5009	0.42834	4.65114	<.001
	LA MEAN ⇒ ID MEAN	0.14077	0.0769	-0.0159	0.2918	0.17538	1.83066	0.067
	AB MEAN ⇒ ID MEAN	-0.34425	0.107	-0.5506	-0.1881	-0.36103	-3.2178	0.001
Total	**OC MEAN ⇒ ID MEAN**	0.30855	0.1146	0.05819	0.5716	0.30205	2.69326	0.007
	HB MEAN ⇒ ID MEAN	0.32151	0.0791	0.18494	0.4825	0.40595	4.06269	<.001
	LA MEAN ⇒ ID MEAN	0.1903	0.0795	0.03394	0.3412	0.23708	2.39392	0.017
	AB MEAN ⇒ ID MEAN	-0.2146	0.1121	-0.4191	-0.0265	-0.22505	-1.9147	0.056
Note. Confidence intervals computed with method: Bias corrected bootstrap								
Note. Betas are completely standardized effect sizes								

Mediation analysis using bootstrapped confidence intervals demonstrates that loss aversion and anchoring bias indirectly influence investment decisions via return perception, whereas overconfidence and herding bias show no significant indirect effects. Direct effects reveal that overconfidence (β = 0.221, p = .034) and herding (β = 0.428, p < .001) positively influence investment decisions, while anchoring bias has a negative direct effect (β = -0.361, p = .001). Overall, total effects show that overconfidence, herding, and loss aversion positively impact investment decisions, highlighting the complex interplay of behavioral biases and mediating perceptions of risk and return.

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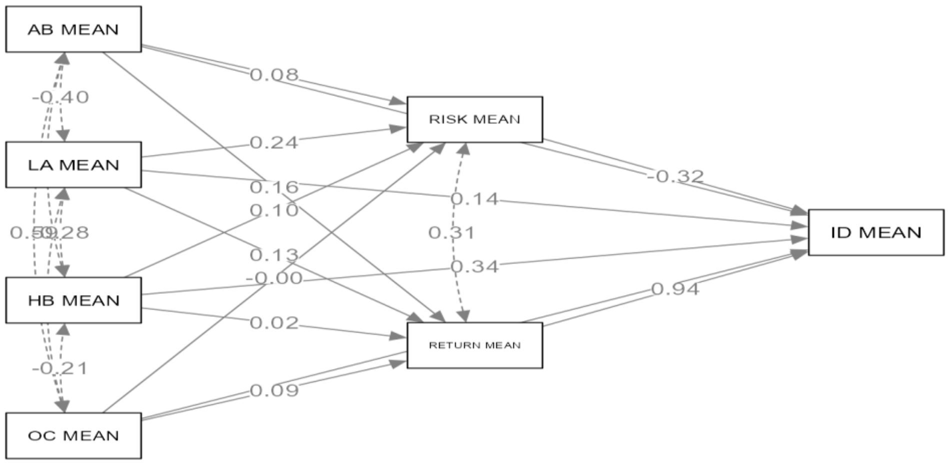


Diagram 1: Path Model- Statistical Diagram

4.2 Discussion

The present study examined the influence of behavioral biases on investment decisions among millennials in Bengaluru, considering risk and return perception as mediators. The findings highlight the significance of behavioral finance in shaping investment behavior, providing both **theoretical and empirical insights** into how different biases influence decision-making in emerging financial markets. This study extends **Prospect Theory** by demonstrating a dual-perceptual mediation model in the context of an emerging market.

4.2.1 Investment Decisions and Behavioural Biases

The results indicate that **overconfidence bias (OC)** and **herding bias (HB)** have a significant **positive direct effect** on investment decisions. Among all biases examined, **herding behavior emerged as the strongest direct determinant**, supporting the predictions of Prospect Theory, which suggests that investors often follow social cues and exhibit herd-like behavior, leading to potentially irrational decisions. This aligns with prior research emphasizing social and informational dependencies among investors (Vijay Kumar Goyal & Sharma, 2023; Sengupta, 2025).

Overconfidence bias was also a significant predictor of investment decisions, corroborating previous studies that demonstrate how investors tend to **overestimate their knowledge and ability** to make rational decisions (Syed Zain ul Abdin, 2022) Notably, the high mean value for overconfidence indicates that millennials in Bengaluru exhibit a pronounced tendency to overvalue their investment capabilities.

In contrast, **anchoring bias (AB)** exhibited a **direct negative effect** on investment decisions, suggesting that reliance on prior reference points may constrain investment behavior. Interestingly, when mediators were included, the effect of AB became marginal, indicating that its influence may be partially transmitted through cognitive evaluation processes. **Loss aversion (LA)**, while not showing a direct effect on investment decisions, exerted an indirect effect via mediators, highlighting its impact through cognitive appraisal rather than direct bias-driven behavior.

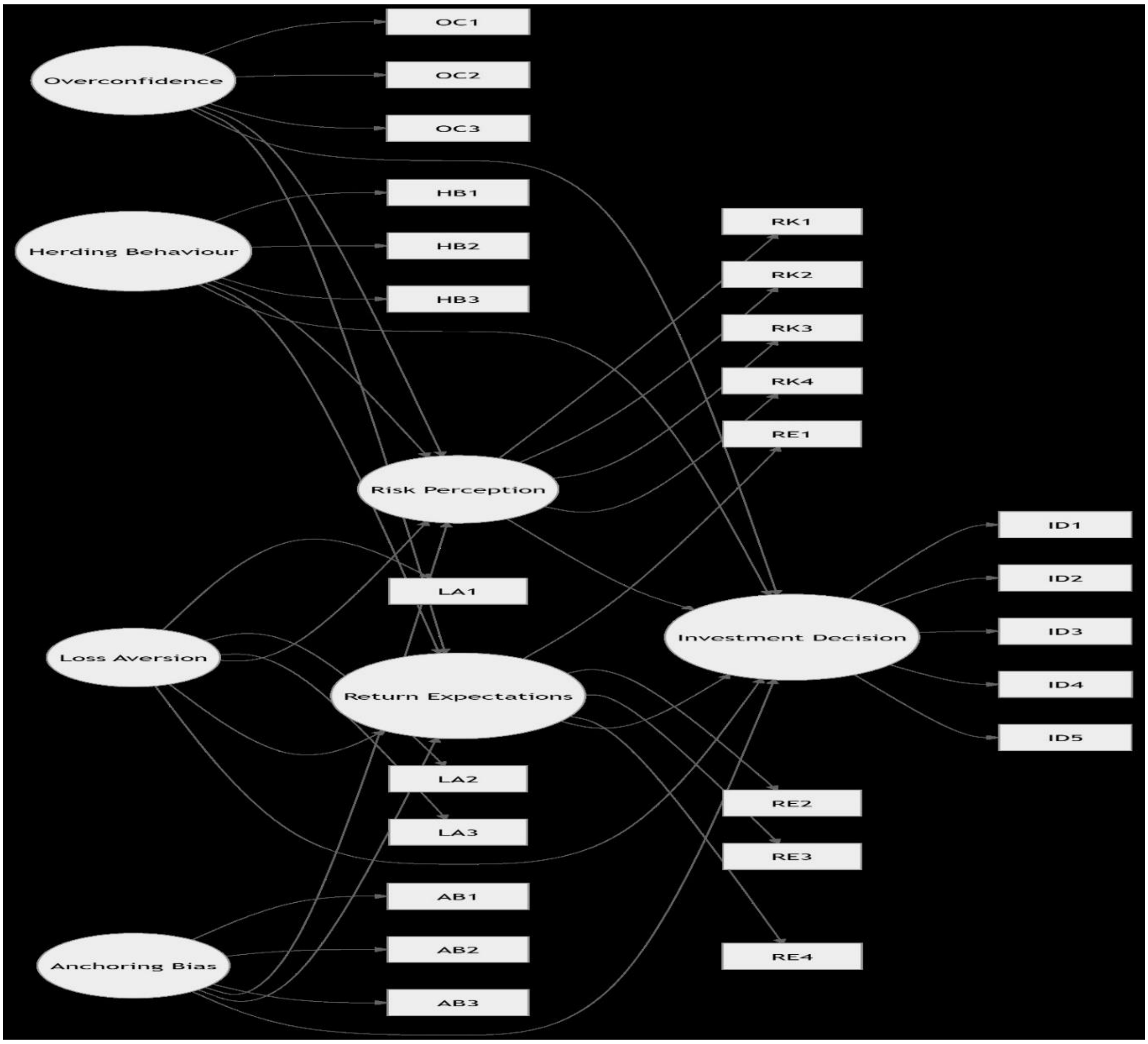
4.2.2 Role of Risk and Return Perception as Mediators

A key contribution of this study is the identification of **risk and return perception as mediators** in the relationship between behavioral biases and investment decisions. **Return perception** emerged as a strong positive predictor (β = 0.494), whereas **risk perception** was a significant negative predictor (β = −0.288), consistent with the classical risk-return trade-off assumption in behavioral finance.

Loss aversion (LA) demonstrated **full mediation** through both risk and return perceptions. This suggests that loss-averse investors are highly sensitive to potential gains and losses, and their investment decisions are strongly influenced by how they evaluate trade-offs between risk and return. **Anchoring bias (AB)** showed **inconsistent mediation**, positively influencing return perception while simultaneously exerting a direct negative effect on investment decisions. This indicates that while AB may elevate return expectations based on reference points, it can constrain decision flexibility among millennial investors.

Conversely, **overconfidence (OC) and herding bias (HB)** did not significantly influence investment decisions via risk or return perception, highlighting a clear distinction between **behaviorally driven biases** (direct impact) and **perception-driven biases** (mediated impact). These findings underscore the nuanced pathways through which different behavioral biases operate in shaping investment behavior in emerging markets.

4.2.3 Conceptual structural equation model showing the effects of behavioral biases on investment decision-making, mediated by risk perception and return expectations.



4.2.4 Theoretical implication: -

This study contributes to the literature in three key ways:

Differentiation of Bias Mechanisms: Behavioral biases do not operate through uniform psychological processes. Loss aversion (LA) functions primarily through perception mediation, whereas overconfidence (OC) and herding bias (HB) are action-oriented and exert direct effects on investment decisions. **Support for Dual-Perception Processing:** The findings reinforce the notion that financial decision-making is guided by dual cognitive pathways. Heuristics-driven biases can operate simultaneously but influence behavior in distinct ways, highlighting the complexity of investor cognition. **Complex Mediation in Anchoring Bias:** The mediation analysis for anchoring bias (AB) reveals conflicting internal mechanisms, indicating that some biases may simultaneously promote and restrict investment behaviors. This underscores the need for further theoretical refinement to capture nuanced behavioral pathways in emerging financial markets.

4.2.5 Practical implications: - For the policy maker and financial advisors: -

For policymakers, financial advisors, and market educators: Millennials are strongly influenced by social cues and peer behavior, suggesting that financial interventions should address group dynamics and community influence. The pronounced overconfidence among investors points to an urgent need for financial literacy programs that encourage accurate self-assessment, calculated risk-taking, and informed decision-making. As return perception is the strongest predictor of investment decisions, communication strategies should emphasize realistic return expectations. Risk education programs should also be implemented to promote rational, evidence-based investment choices. Structured advisory and educational interventions can help mitigate direct behavioral biases while enhancing perception-driven decision-making.

4.2.6 Limitations and Future Research

The study is limited to millennials in Bengaluru, which may reduce the generalizability of the findings. Future studies should compare urban and rural investors to examine contextual differences. Longitudinal research could assess whether behavioral biases evolve across different market cycles. Incorporating variables such as financial literacy, income volatility, or market experience could provide deeper insights into the conditions under which biases exert stronger e

4.2.7 Ethical considerations: -

The study is conducted as per the ethical standards. The participation was voluntary with consent from all respondent. The data was treated highly confidential and participant's privacy is protected.

5. Conclusion

Overall, the findings confirm that **behavioural biases exert a significant influence on investment decisions**, but they operate through **distinct mechanisms**. Herding bias (HB) and overconfidence bias (OC) have **direct and positive effects** on investment decisions, reflecting action-oriented behaviours. In contrast, loss aversion (LA) functions primarily through **risk and return perceptions**, highlighting the importance of cognitive mediation in shaping decision outcomes. Anchoring bias (AB) demonstrates **competing pathways**, exerting a positive effect through return perception while simultaneously showing a direct negative influence on decisions. Among the cognitive mediators, **return perception emerged as the strongest driver**, whereas **risk perception serves as a significant deterrent**, consistent with classical and behavioural finance theories. These findings underscore the necessity of **integrating behavioural and cognitive perspectives** to accurately capture the investment behaviour of millennials in emerging markets.

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Competing Interests

The author(s) declare that they have no known financial or non-financial competing interests that could have influenced the work reported in this paper.

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