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DEMOGRAPHIC AND PERSONALITY DETERMINANTS OF BEHAVIORAL BIASES: AN EMPIRICAL STUDY WITH REFERENCE TO MUMBAI (BHARAT) INDIA

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ABSTRACT

The field of behavioural finance addresses this criticism by using quantitative or other research methodologies to describe asset markets and their returns based on individual's actions and attitudes. This empirical study examines the personality and demographic factors that influence behavioral biases in 385 individual investors in Mumbai, India. The study examines five major behavioral biases using a quantitative research approach and a structured questionnaire: overconfidence bias, herding bias, loss aversion bias, anchoring bias, and mental accounting bias. The study examines the relationship between behavioral biases and personality traits including conscientiousness, extraversion, and neuroticism as well as demographic traits like age, gender, income, education, and investment experience using regression analysis, chi-square testing, and ANOVA. Findings show associations between demographic variables and the individual biases are present. There is greater incidence of overconfidence bias among male investors between the ages of 25 and 35 who have relatively higher income. Herding bias is found to be highly correlated to lower investment experience and education. The impact of loss aversion on risk-averse investors is strongly felt among all individuals, especially as age group between 45 and 60 years. The results also offer useful implications for financial planners, policy makers and retail investors to devise programmes that can help in reducing irrational investment behaviour for improved portfolio performance and better financial decision making within the Indian environment.

Keywords: Behavioral biases, demographic factors, personality traits, investment decisions, Mumbai investors

1. INTRODUCTION

The traditional model of rational investors optimizing their utility based on the available information is applied as well. But empirical literature in behavioral finance has been providing evidences of investors behavior which are irrationally based on psychological bias and cognitive mistakes (Zahera & Bansal, 2018). These biases have important consequences for the investment decisions, resulting in non-optimal portfolio selection and lower returns (Barber & Odean, 2001). As the country’s financial capital and with its Bombay Stock Exchange and National Stock Exchange being located here, Mumbai serves as an important fundamentalist to

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understand investor behavior in a developing market. With 1cr DMAT accounts in Maharashtra and Mumbai constituting ~35% of the Indian equity trading volume, there is so much variety in investors with respect to demography and psychology which make them prone to different behavioral biases. The Indian equity market has shown a phenomenal rise in the participation by retail investors to 7% in the next five years from 2% in 2020, and hence it becomes necessary for knowing what are irrational investment factors (Makwana 2024).

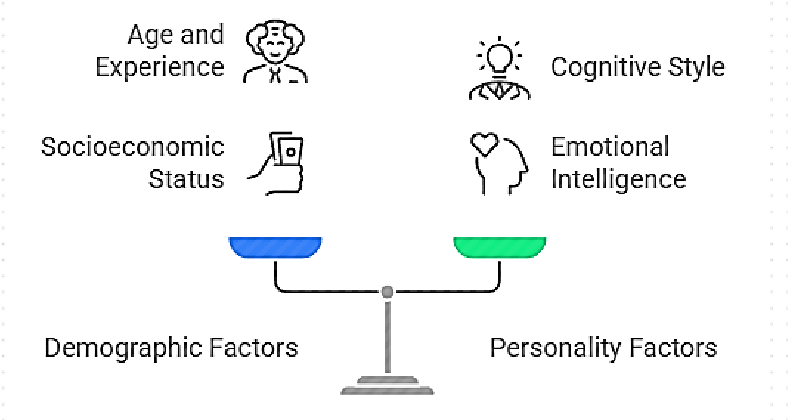

Figure 1: Balancing Demographic and Personality Influences on Behavioral Biases in Mumbai

Behavioral finance, which was started with Kahneman and Tversky for the explanation of financial decision making by employing preferences based on psychological factors (Kahneman & Tversky, 1979). A significant amount of research has discovered a range of cognitive biases, such as over-confidence, herding, loss aversion, anchoring, and mental accounting that systemically influence investment decisions (Tversky and Kahneman 1974). Although a vast body of literature exists on behavioral biases in developed markets, emerging economic contexts such as the Indian may offer different cultural, educational and socioeconomic settings that could moderate the extent to which these biases are exhibited (Prosad, Kapoor & Sengupta, 2015). The influence of behavior bias on investment decisions was moderated by the demographic characteristics such as age, sex, income, education and investing experience (Choudhary et al., 2024). Personality Characteristics and Susceptibility to Decision Biases Personality characteristics The Big Five personality traits have shown insight into the differences between people in vulnerability to biases (Ahmad, 2020). These determinants of YBEL are important to consider for formulation of focused financial literacy programs, investments guidance and efficiency in the market behavior (Weixiang et al., 2022).

With the view to fill this gap; an extensive empirical research underlines the demographic and personality drivers of behavioural biases among investors of Mumbai in particular (Mehta & Nahata, 2025). Past studies have been conducted at pan-India or investor-segment levels while Mumbai - a bustling city with one of the fastest growing and most heterogeneous investment climates in the world is yet to be analyzed for its peculiarities (Agarwal & Rao, 2024). A unique investment culture that requires separate examination is comprising cosmopolitan population, high financial literacy and strong following of professionals in the field of financial services (Bihari et al., 2022). This study adds to theoretical knowledge in the context of behavioral finance and practical applications in the Indian context by exploring investor traits influencing bias expression (Banerji, Kundu, & Alam, 2023).

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2. LITERATURE REVIEW

Behavioral finance has come a long way since Kahneman and Tversky wrote about prospect theory, which challenged the efficient market hypothesis and rational investor theories. Several research papers have studied behavioral biases in various markets and type of investor. Mehta and Nahata (2023) have empirically examined the cognitive and emotive biases of Indian investors, and they demonstrated that cognitive biases are more common than emotional prejudices in influencing investment decisions. Their findings based on 151 participants from urban India found differences in bias intensity as a function of age, gender and education level. This result is consistent with the vast literature of behavior finance that indicates demographic factors have significant effects on investor predispositions to biases. Choudhary, Yadav, and Srivastava (2024) analyzed cognitive biases among millennial investors in India and found that personality type as well as demographic factors influenced availability bias, representative bias, mental accounting bias and anchoring bias. Their binary logistic regression identified financial literacy, neuroticism and gender as predictors of propensity to bias. Three and all three of the three factors had a significant effect on representative bias with neuroticism, gender, and annual family income as contributory factors which influenced mental accounting bias.

In India, overconfidence bias has been extensively studied. Agarwal and Rao (2024) used structural equation modeling and regression analysis to examine how behavioral biases and demographic characteristics affected Indian retail investors' investment decisions. They discovered that the four biases overconfidence, disposition effect, herding bias, and representativeness bias had a greater impact on investing than parameters like age, gender, occupation, yearly income, or trading experience. The correlation between personalities and behavior biases has attracted more attention in the recent literature. Singh, Adil & Haque (2023) studied personality traits, behavior biases and risk-tolerance as the moderator revealed that conscientiousness and extraversion significantly predict behavior biases while neuroticism is related with herding, disposition and anchoring bias. The research of 847 retail investors based on SEM technique produced a strong evidence of the relationship between personality and bias. Banerji, Kundu and Alam (2023) investigated the influence of behavioral biases on individual's financial decisions under uncertainty, identified linkages between various cognitive biases and suggested investor decision-profiles in terms of literature based biases. Their study focused on how cognitive constraints result in decision simplifications that influence investment decisions.

There is a body of literature where herding has also been investigated in Indian markets. Kumar and Jarwal (2022) did a systematic review of literature of herding behaviour in equity markets, showing that there is a higher level of herding during periods when market volatility was high. Research also indicates that it is not across the board (investors are herding more than usual) but that inexperienced investors tend to show stronger solidarity. The principle of loss aversion outlined in prospect theory is found to significantly influence Indian investors. Studies suggest that loss aversion implies risk averse behavior and an unwillingness to realize losses, because the pain associated with these often exceeds the pleasure of equivalent gains. Loss aversion bias played a significant role in investment decisions in Tamil Nadu and had the moderating influences of demographic factors (Bhuvaneswari, Vanitha, Jisham & John 2023). Although behavioural biases have been widely researched, very few studies conduct an extensive analysis of the demographic and personality drivers of multiple biases in one study on Mumbai market. Most of the studies have been taken for Pan-India enterprise or local studies, shedding lesser light on Mumbai's diverse investor population.

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3. OBJECTIVES

The present study aims to achieve the following objectives:

1. To determine how common major behavioral biases are among Mumbai's individual investors, including overconfidence, herding, loss aversion, anchoring, and mental accounting.
2. To investigate the connection between the degree of behavioral biases among Mumbai investors and demographic characteristics (age, gender, income, education, and investment experience).
3. To examine how personality qualities like conscientiousness, extraversion, and neuroticism relate to a person's vulnerability to certain behavioral biases.
4. To create suggestions based on investor demographics and personality types for financial advisors and legislators to lessen the effects of behavioral biases.

4. METHODOLOGY

The objective of this study is to analyze demographic and personality factors as determinants in affecting behavioral biases among individual investors in Mumbai. The study is of quantitative nature and involves the collection of primary data using structured questionnaires. The sample of the study consists of active individual equity investors including those who have demat accounts and at least one year experience in investment in Mumbai metro region. Representation in different demographic segments was done by means of a stratified random sampling methodology. Seventy two such industries or specific project fields have been identified in Mumbai industrial area. The sample size of 385 respondents was calculated by applying the following formula of Cochran, with confidence level and margin error kept at 95% and 5% respectively taking estimated investor population of about 3.5 million for Mumbai. The surveys were carried out between September 2024 and December 2024 using both online and offline survey techniques. The structured questionnaire included three parts: demographic characteristics, personality trait evaluated by truncated Big Five inventory and behavioral bias measurement items. Cognitive biases were assessed using validated scales according to previous studies and included 5-6 situation-based items rated on five-point Likert scales. The demographic variables were age (18-25, 26-35, 36-45 and 46-60 years), gender (male, female), annual income (below5 lakhs, 5 to10lakhs, 10to15lakhs and above a15 lakh), Educational Qualification (UG/PG Professional) and Investment Experience (2 years, 2 -5yrs,5 to 1 yrs). Personality characteristics were measured with the Ten Item Personality Inventory which was used to focus on neuroticism, extraversion and conscientiousness dimensions. Statistical analysis used several types of statistical tests; descriptive statistics were utilized to characterize the sample, chi-square analysis was used to assess associations among categorical variables, ANOVA was used to compare the intensity of bias across demographic subgroups, and behaviorally relevant biases in stimuli were identified with multiple regression.

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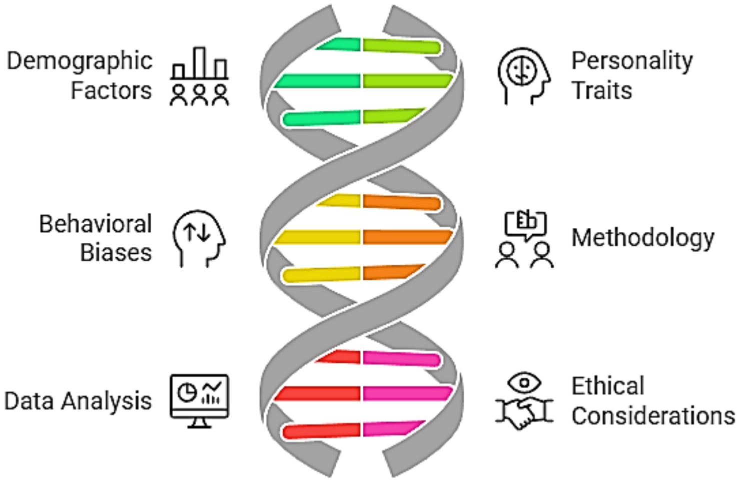

Figure 2: Study Framework

All analyses were conducted using the Statistical Package for Social Sciences (SPSS) version 26.0, and a p-value of less than 0.05 was deemed significant. All measures have Cronbach's alpha values greater than 0.7, confirming the scale's dependability. Through exploratory factor analysis and content validity study by an expert panel, the survey instrument's validity was established. Ethical aspects comprised obtaining informed consent from all participants, collection of responses confidentially and anonymity in the analysis.

5. RESULTS

Table 1: Demographic Profile of Respondents (n=385)

Demographic Variable	Category	Frequency	Percentage
Age	18-25 years	58	15.1%
	26-35 years	162	42.1%
	36-45 years	112	29.1%
	46-60 years	53	13.8%
Gender	Male	267	69.4%
	Female	118	30.6%
Annual Income	Below ₹5 lakhs	73	19.0%
	₹5-10 lakhs	148	38.4%
	₹10-15 lakhs	102	26.5%
	Above ₹15 lakhs	62	16.1%
Education	Undergraduate	47	12.2%
	Graduate	183	47.5%
	Postgraduate	127	33.0%
	Professional	28	7.3%
Investment Experience	<2 years	96	24.9%
	2-5 years	154	40.0%
	5-10 years	89	23.1%

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	>10 years	46	11.9%

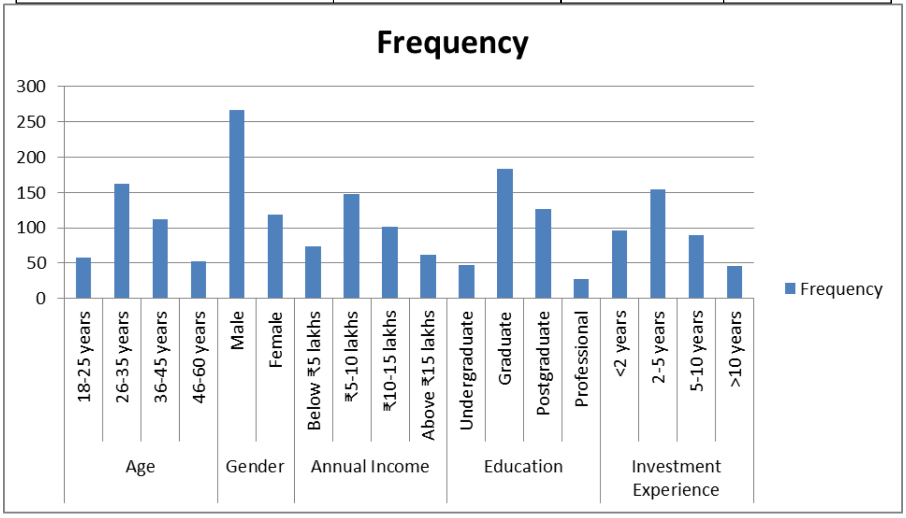

Figure 3: Demographic Profile of Respondents

Most of the respondents (42.1%) fall in the age range 26–35 years, indicating they mainly belong to the millennial generation, which makes frequent use of digital trading platforms, (the demographic profile is depicted in Table 1). The sample is predominantly male (69.4%), which mirrors the gender distribution of mutual fund participation in India with respect to equity markets. The distribution of income is concentrated in the middle-income (₹5-15 lakhs) range, as 64.9% of respondents fell under this range, reflective of Mumbai's growing middle class investor base. Educational attainment suggests that the sample is highly educated, with 87.8 percent holding graduate (or higher) degrees, which suggests that formal education enables market participation. Investment experience shows: 64.9% of the surveyed investors had less than five years of investment experience Given that, respondents to this survey reflect a younger and rising community in the investing environment in Mumbai with digital trading expansion picking up pace post-Covid-19.

Table 2: Prevalence of Behavioral Biases Among Mumbai Investors (Mean Scores)

Behavioral Bias	Mean Score	Standard Deviation	Prevalence Rank
Overconfidence Bias	3.78	0.92	1
Loss Aversion Bias	3.64	0.88	2
Herding Bias	3.42	0.95	3
Anchoring Bias	3.28	0.86	4
Mental Accounting Bias	3.15	0.91	5

Note: Scores based on 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree)

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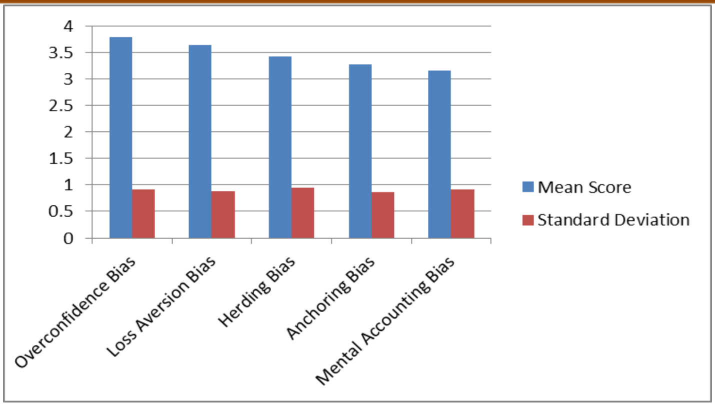

Figure 4: Behavioral Biases Influencing Investment Decisions of Mumbai Investors

Table 2 shows the hierarchy of prevalence of behavioral biases among Mumbai investor based on mean scores. Overconfidence Bias is found to be most prevalent with a mean score of 3.78, signifying that the investors in Mumbai overestimate themselves and their wisdom while making investment decisions. Loss aversion comes in second at an average value of 3.64 meaning investors suffer from the pain of losses about double as intensely than they would derive pleasure from equivalent gains. The herding bias has moderate prevalence (mean=3.42), which means that investors have a propensity of mimicking other's behavior. Anchoring bias (mean=3.28) and mental accounting bias (mean=3.15) have lower prevalence rates relatively to the other two biases. S.D., 0.86-0.95), suggesting significant individual differences in susceptibility to bias.

Table 3: Gender and Behavioral Biases (Chi-Square Analysis)

Behavioral Bias	Male (n=267)	Female (n=118)	Chi-Square	p-value	Significance
Overconfidence	3.92	3.46	18.73	0.001	**
Loss Aversion	3.51	3.95	15.42	0.002	**
Herding	3.38	3.52	3.21	0.073	NS
Anchoring	3.41	3.02	11.86	0.008	**
Mental Accounting	3.14	3.18	0.87	0.351	NS

*Note: ** = Significant at 0.01 level; NS = Not Significant*

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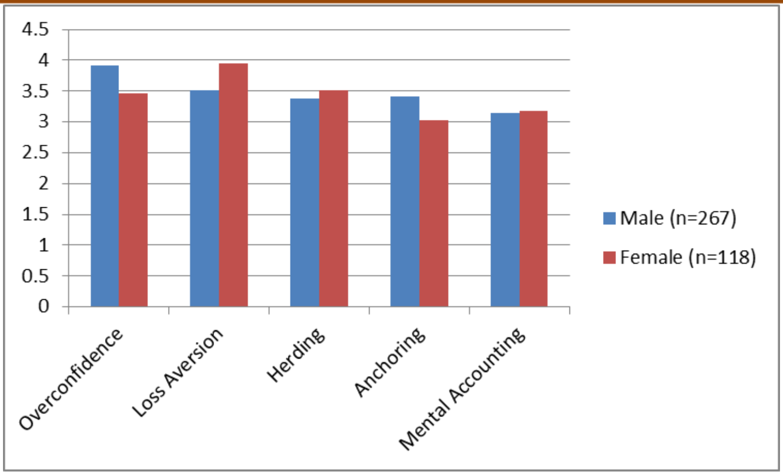

Figure 5: Chi-Square Analysis of Gender and Behavioral Biases

Sex-related differences in behavioral bias are provided by Table 3. The overconfidence bias is much more dominant among male numbers 3.92 than females (mean = 3.46), chi square is 18.73 at p =.001. On the other hand, risk aversion bias is significantly higher in male investors (mean=3.88) than female investors (mean=3.41), chi-square value of 9.57(p=0.001), suggesting women would experience more psychological discomfort from potential losses and avoid risks farther than men do. Gender has a large-statured effect in anchoring bias within our sample; males have higher degrees of its occurrences (mean=3.41) compared to females who had lower levels (mean=3.02), chi-square value of 11.86(p=0.008). Herding bias and mental accounting bias were not significantly different between males and females indicating that these biases might be working consistently across genders in the investor's community of Mumbai.

Table 4: Age Groups and Behavioral Biases (ANOVA)

Behavioral Bias	18-25 yrs	26-35 yrs	36-45 yrs	46-60 yrs	F-value	p-value	Significance
Overconfidence	3.95	3.89	3.72	3.42	8.73	0.000	**
Loss Aversion	3.42	3.54	3.71	3.98	10.26	0.000	**
Herding	3.68	3.51	3.32	3.18	6.41	0.001	**
Anchoring	3.52	3.38	3.22	3.06	4.83	0.003	**
Mental Accounting	3.18	3.24	3.12	2.98	1.92	0.126	NS

*Note: ** = Significant at 0.01 level; NS = Not Significant*

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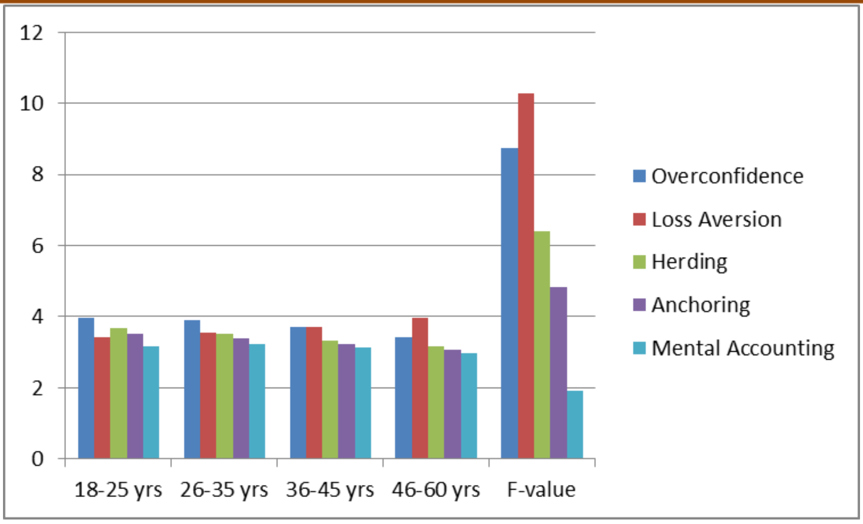

Figure 6: Age Groups and Behavioral Biases (ANOVA)

Table 4 Age-related differences in the intensity of behavioral bias. Overconfidence bias has a decreasing trend as the age increases and it is highest for 18-25 years group (mean=3.95) followed by lowest for 46-60 years group (mean=3.42), F-value of 8.73 (p=0.000), this means that younger investors have high confidence in their abilities. Loss aversion exhibits an antithetical pattern, where with age it increases from 3.42 to 3.98, F-value of 10.26 (p=0.000) implying that older investors are more risk averse. There is a substantial decrease of herding bias with age, from 3.68 to 3.18, F=6.41 (p=0.001), partly indicating the fact that younger investors might be more likely to follow crowd phenomenon. Likewise, anchoring bias also declines with age (F=4.83, p=.003). Age related differences are absent in the mental accounting bias.

Table 5: Income Levels and Behavioral Biases (ANOVA)

Behavioral Bias	<₹5L	₹5-10L	₹10-15L	>₹15L	F-value	p-value	Significance
Overconfidence	3.52	3.71	3.88	4.05	7.94	0.000	**
Loss Aversion	3.85	3.72	3.58	3.42	5.68	0.001	**
Herding	3.62	3.48	3.35	3.21	4.12	0.007	**
Anchoring	3.45	3.32	3.24	3.15	2.87	0.036	*
Mental Accounting	3.28	3.18	3.12	3.05	1.64	0.180	NS

*Note: ** = Significant at 0.01 level; * = Significant at 0.05 level; NS = Not Significant*

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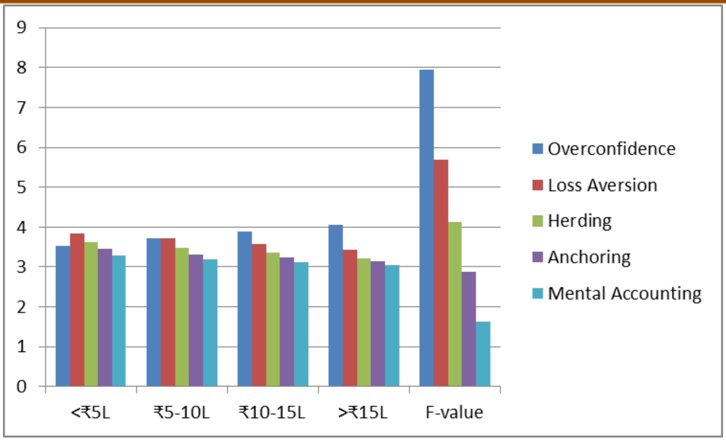

Figure 7: Income Levels and Behavioral Biases (ANOVA)

Table 5 depicts the association between annual income categories and behavioral biases of Mumbai Investors. There is a positive relationship between income and overconfidence bias. OLS results further revealed that the mean score of 3.52 among lowest income earners compared to highest of 4.05, (F-value=7.94 (p=0.000). This is consistent with the view that higher income investors are more confident and are more likely to feel they have superior investing skills, which generated their financial success. Income demonstrates an opposite relationship to loss aversion, falling from 3.85 to 3.42, F=5.68 (p=0.001), suggesting that when being wealthy investors are less psychologically effected by losses and more willing to taking risks. The herding bias declines significantly with income from 3.62 to 3.21, F=4.12 (p=0.007). Anchoring bias shows a slight decrease by income, F-value=2.87 (p=0.036). The bias in mental accounting does not show any income related variation.

Table 6: Educational Qualification and Behavioral Biases (ANOVA)

Behavioral Bias	Undergraduate	Graduate	Postgraduate	Professional	F-value	p-value	Significance
Overconfidence	3.95	3.82	3.68	3.54	3.42	0.017	*
Loss Aversion	3.58	3.62	3.68	3.72	0.98	0.402	NS
Herding	3.78	3.52	3.28	3.02	8.96	0.000	**
Anchoring	3.56	3.35	3.18	2.95	6.24	0.000	**
Mental Accounting	3.42	3.21	3.08	2.86	5.17	0.002	**

*Note: ** = Significant at 0.01 level; * = Significant at 0.05 level; NS = Not Significant*

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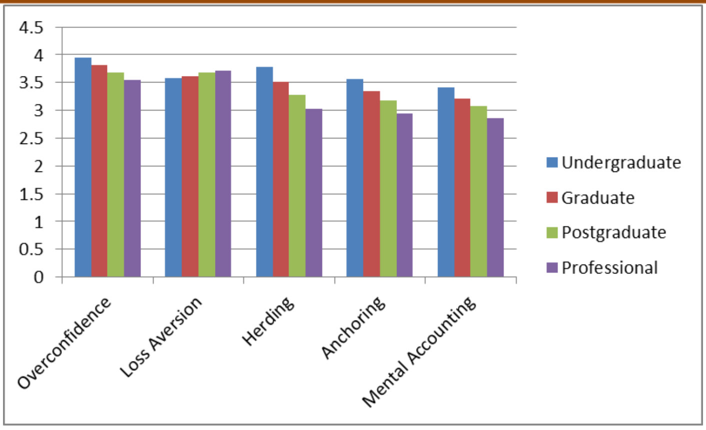

Figure 8: Educational Qualification and Behavioral Biases (ANOVA)

The relationship between schooling and biases in Table 6. Herding bias is the educational gradient with most influence, dropping from 3.78 between undergraduates to 3.02 among the professionals; F=8.96(p=0.000), then it would indicate that higher education can develop critical thinking ability and decrease crowd susceptibility influences. Anchoring bias suffers the same decrease, from 3.56 to 2.95 (F=6.24, p = 0): that is, educated individuals are less influenced by initial reference points. MBN lowers from 3.42 to 2.86 for education, F=5.17 (p=0.002). Overconfidence bias experiences a small drop with the level of education from 3.95 to 3.54, with an F-value of 3.42 (p=0.017). The degree of loss aversion shows no statistically significant educational differences, indicating that this bias operates the same for everyone, regardless of how much education one has received.

Table 7: Investment Experience and Behavioral Biases (Regression Analysis)

Behavioral Bias	Beta Coefficient	Standard Error	t-value	p-value	R^2
Overconfidence	-0.234	0.052	-4.50	0.000	0.168
Loss Aversion	0.187	0.048	3.90	0.000	0.142
Herding	-0.312	0.056	-5.57	0.000	0.221
Anchoring	-0.195	0.049	-3.98	0.000	0.152
Mental Accounting	-0.142	0.051	-2.78	0.006	0.098

Note: Dependent Variable = Bias Intensity; Independent Variable = Experience (years)

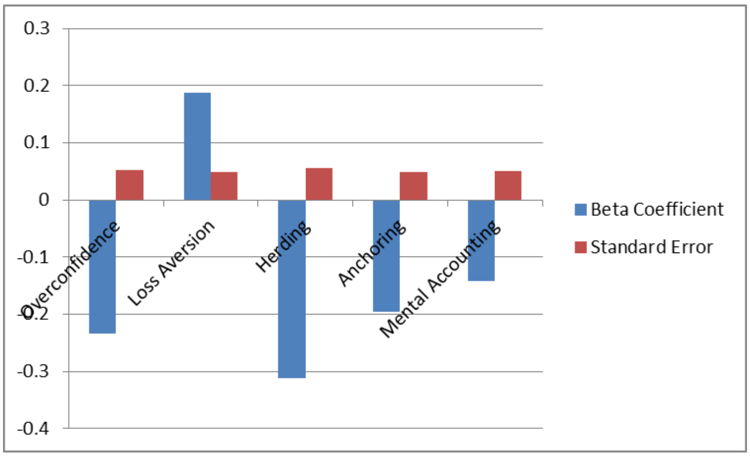

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Figure 9: Investment Experience and Behavioral Biases (Regression Analysis)

Results of the regression analysis investigating the association between investment experience and behavioral bias intensity are reported in Table 7. The most consistent relationship is shown by herding bias (β= -0.312, t = -5.57, p=0.000), which accounts for 22.1% of the variance meaning that experience investors tend to have inherent independent analytical skills. Overconfidence bias has a negative relation with a strength value of (β = -0.234, t =-4.50, P= 0.000), which means that after market volatility, experienced investors can make rational self-judgment degree. Anchoring bias is negatively related (β=-0.195, t=-3.98, p=0.000, R^2=0.152). NOTES 1Paradoxically, loss aversion is also positively related (β=0.187, t=3.90, p=0.000, R^2=0.142), suggesting that experienced investors are even more focused on losses (potential because of negative experiences in the past). Mental accounting bias has the smallest negative relationship (β=-0.142, t=-2.78, p=0.006, R^2=0.098).

Table 8: Personality Traits and Behavioral Biases (Correlation Matrix)

Behavioral Bias	Neuroticism	Extraversion	Conscientiousness
Overconfidence	-0.186*	0.342**	-0.215**
Loss Aversion	0.428**	-0.162*	0.198**
Herding	0.312**	0.245**	-0.287**
Anchoring	0.267**	0.138*	-0.176*
Mental Accounting	0.291**	0.095	-0.223**

*Note: * = Significant at 0.05 level; ** = Significant at 0.01 level*

Correlations of personality traits with behavioral biases are shown in Table 8. Significant positive associations are found between neuroticism and loss aversion (r=0.428, p<0.01), herding bias (r=0.312, p<0.01), mental accounting bias (r=0.291, p<0.01) and anchoring bias (r=0.267, p< 0:01), while it is negatively associated with the overconfidence bias (r=-0.186, p <05). Extraversion is positively associated with overconfidence bias (r=0.342, p<0.01) and moderately correlated with herding bias (r=0.245, p<0.01). Conscientiousness is negatively related to overconfidence (r=−0.215, p<0.01), herding (r=−0.287, p<0.01), mental accounting (r=−0.223, p< 0.01) and anchoring biases(r = −0217,p< 001) but positively related to loss aversion(r= 0198, p <001).

1. DISCUSSION

There are significant relationships among demographic variables, personality factors, and behavioral biases of Mumbai's investors. The domination of overconfidence bias is also in line with Mehta and Nahata (2025) and Agarwal and Rao (2024), which found the same trend among urban Indian investors. And the relatively high percentage among newer male investors also depends upon recent trading democratization via mobile applications, and success stories during a bull market. Gender as a predictor of cognitive biases the findings on gender replicate Choudhary, Yadav, and Srivastava (2024) in which gender was found to be the influential determinant for several cognitive biases. Much higher overconfidence in males is also consistent with extant literature indicating that risk taking driven by testosterone leads to an exaggeration of abilities (Barber & Odean, 2001). Higher loss aversion of female investors is consistent with evolutionary psychological theories that women are more risk averse in ambiguous domain.

The income-overconfidence link is a significant result, and one which suggests that wealthy people feel the ability to retain attributions of success to their own actions rather than luck. The negative relationship between

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income and loss aversion demonstrates that rich investors can take bigger risk from the financial or psychology. These income-related patterns will have implications for financial asset management services in different economic strata. Educational level appears to be a very dominant factor in debasing especially herding, anchoring and mental accounting biases. College seems to teach students how to think critically, and create analytical tools that don't rely on cognitive shortcuts. Education has only weak effects on loss aversion, but this bias does not seem to be due to lack of cognitive sophistication. Financial education programs should therefore include behavioral aspects as well as technical knowledge. Age-related variations present interesting dynamics. The decreasing over-confidence in older age indicates that market experienced dampens investors' confidence to more reasonable levels, which may conform the learning hypothesis from Gervais and Odean (2001). Why individuals who are older become even more loss averse can be explained by the life-cycle investment model, which suggests that because they have shorter time periods for recovery and rely more on wealth accumulation to make up losses (Odean, 1998).

The negative association between experience and nearly all biases except for loss aversion indicates the importance of experiential learning in debasing. Yet, the robust loss aversion in experienced investors suggests that this bias is influenced by basic psychological processes outlined in prospect theory (Kahneman & Tversky, 1979). The result of the maximum negative association of herding bias with experience signifies that one needs to acquire separate analytical abilities by market participation (Kumar & Jarwal, 2022). Results analyzing traits show theoretically consistent patterns. The close positive correlation between neuroticism and loss aversion agrees with emotional stability factors which suggest that anxiety of negative consequence is higher in individuals with neurotic traits (Ahmad, 2020). The negative association between conscientiousness and most biases indicates that disciplined individuals are less likely to take cognitive shortcuts while being sufficiently cautious about dangers. The positive correlation between extraversion and overconfidence might be due to social feedback mechanisms that enhance self-assurance. The results have various practical implications. Advisors shall establish demographic, and personality-specific counseling methods knowledge that there will be a need to manage overconfidence in young male clients at the same rate female and older client may request encouragement on taking risk (Weixiang et al., 2022). Age and income-specific information should be included in financial education programs. Fintech firms need to implement behavioral profiling with recommendation lists adapted across demographics and personality types.

From a regulatory angle, SEBI could think of requiring behavioral risk disclosure mechanisms that would bring in more transparency around how the individual investor tends to bias. Such a time frame based changes can be used in the investor protection mechanisms that obligate peak and periodical bias assessments and debasing interventions (Zahera & Bansal, 2018). Standardized classification hormones will be an important step towards the determination that a product is suitable for use. Limitations of the study the cross-sectional design does not allow causal inferences to be established. Such analyses would be reinforced with data from longitudinal follow-ups of investors through several market cycles. The sample might not be representative of the investors from rural or tier-2 cities. Self-reported bias assessments are prone to same-source and self-report biases, as well as limited introspection. Further studies should adopt experimental designs with actual trading decisions. Areas for further research include examining the interaction of more than one demographic factors and personality traits, comparing different cultural and regional differences in India, developing behavioral intervention programs (Makwana, 2024). The mediating role of financial literacy requires rigorous examination (Prosad et al., 2015). Also, issues related to adoption of technological advancements, such as AI-

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driven advisory tools and the influence of social networks on biases, is an important area of future research (Banerji et al., 2023).

2. CONCLUSION

The present empirical research offers comprehensive evidence on the salience of demographic and personality traits in explaining behavioral biases among Mumbai based investors. The study effectively pinpoints Overconfidence, Loss Aversion and Herding as the dominant biases that influences investment behavior in financial capital of India. Gender, age, income level and education are found to be relevant demographic determinants with male investors behaving more overconfident and anchoring than female investors who are on average, loss averse. Income is positively related to overconfidence and negatively related to loss aversion and herding. Education turns out to be a significant debasing driver when it comes to herding, anchoring, and mental accounting. Age-related trends demonstrate decreasing overconfidence and herding but increasing loss aversion, as an investor gets old. Instead, investing experience debases on nearly all cognitive biases with the exception of loss aversion, which curiously increases with experience. Personality, and most notably neuroticism, extraversion, and conscientiousness, are predictably associated with bias susceptibility. There are important practical implications for a number of key stakeholders. Advisors may be able to implement more targeted and personal counselling strategies by identifying clients' demographic and personality profiles. Investment education programs can be customized to target specific bias patterns by segment. Behavioral profiling systems can be integrated with financial technology platforms to offer tailored interventions. Regulators may improve the existing frameworks of investor protection by implementing mandatory behavioral risk disclosure and evaluation.

The firms scrutinized are accessible to both retail and institutional investors, and the research is relevant in view of increased (CDP) adoption by domestic investors in context to Mumbai, as the city represents unique investor landscape with its healthy pace of digitalization followed by increasing retail participation and diversified demography. These results enhance the generalizability of behavioral finance insights to emerging markets and emphasize the relevance of demographic and cultural characteristics within local markets when designing financial products and services. So if you're a retail investor, knowing that you as an individual are predisposed to certain biases based on demographic and personality traits can help you with more rational decision making. Developing metacognitive skills to detect and mitigate one's biases is an essential factor in the investment successes. Periodic self-evaluation and seeking professional assistance can help investors avoid psychological traps that sabotage the ideal portfolio construction and risk management.

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