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IMPACT OF DEMOGRAPHIC FACTORS AND FINANCIAL LITERACY ON BEHAVIOURAL BIASES OF INDIVIDUAL INVESTORS IN INDIA

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Abstract

Purpose: The aim of this paper is to identify the relationship between demographic factors (gender, marital status , age, income, occupation, education, investment experience) and financial literacy and different behavioural biases.

Research Methodology: The study uses one way ANOVA, t- test, multiple regression analysis to investigate the survey data collected from 515 individual investors. the research used purposive and snowball sampling to collect the data.

Findings: the result of multiple regression revealed that demographic characteristics and financial literacy highly influence overconfidence, representativeness, anchoring, mental accounting, loss aversion and disposition bias. Age, occupation, investment experience, and financial literacy are found to be the most prevalent demographic variables associated with the behavioral biases of individual investors.

Research Implications: This research can improve the efficacy of financial services, enable investors to make more informed choices, and promote overall financial well-being. This research will be beneficial for policy makers, financial organizations, financial advisors and individual investors.

Originality: Through the comprehensive literature review, it is found that limited researches have been done to identify the relationship between demographic variables, financial literacy and behavioural biases. Therefore, this study is conducted to the existing research gap in the field of bahvioural finance.

Keywords: Behavioural Biases, Demographic Factors, Financial Literacy, Indian Individual Investors.

Introduction

Conventional financial theories were unable to effectively account for stock market irregularities and disruptions. These disturbances manifested as market bubbles and instances of both underreactions and overreactions. As a result, the field of behavioral finance emerged, aiming to elucidate these irregularities. Behavioral finance links financial decision-making to the psychology of investors. Shiller's 2002 research revealed that efficient market models were insufficient in explaining the extent of stock market volatility. Furthermore, it concluded that there is no comprehensive efficient market model in the stock market as a whole. Shiller further elucidated that bubbles arise as a result of feedback theory, which demonstrates that investors exhibit irrational behavior. Such feedback indicates that human assessments of the likelihood of future occurrences influence their actions.

Behavioral finance asserts that investment behavior is influenced by cognitive, emotional, and psychological factors (Barberis & Thaler, 2003; Chaffai & Medhioub, 2014). Age, income,

education level, investing intent, risk appetite, and other factors can contribute to individual variances (Choudhary, 2016). Multiple research (Adil et al., 2021; Baker et al., 2018) have demonstrated that investment behavior is significantly influenced by demography.
This research investigates the presence of behavioral biases among stock investors in India. Research especially investigating behavioral finance in India is insufficient. Individual investors exert considerable influence on the Indian economy by investing in the stock market at a significantly higher rate than through mutual funds (Ramadorai, 2013).

Despite a substantial corpus of literature on behavioral finance, there is a deficiency of academic inquiry into the relationship between financial literacy and behavioral biases, especially in India (Sahi and Arora, 2012). This study seeks to fill the current void in the behavioral finance literature. India is one of the fastest-growing economies in the world. Individual investors are attracted to Indian financial markets because of its extensive scope and great efficiency. Market regulators and policymakers are concerned about the behavioral tendencies of individual investors. The research employs survey data collected from 497 investors in the Indian stock market to acquire an alternative perspective. Lin (2011) contends that primary data offer a more accurate depiction of investors' behavioral inclinations in investing decision-making than secondary data. The study seeks to investigate three main objectives related to Indian investors: first, to determine the presence of behavioral biases; second, to analyze the relationship between demographic characteristics and behavioral biases; and third, to assess the connection between financial literacy and behavioral biases.

Prior studies examining the relationship between financial literacy or demographics and behavioral biases predominantly focus on Western countries, with no attention afforded to Indian investors. Nonetheless, the financial services sector in India has become very diversified, providing a wide range of investment and savings options. Indian investors, constrained by restricted capabilities and insufficient financial literacy, depend on personal opinions and preferences instead of doing thorough evaluations and comprehending financial goods when making investment selections. An analysis of the behavior of individual investors in India is necessary. This study seeks to bridge the information gap and contribute significantly to the literature on behavioral finance.
The subsequent sections of this inquiry are structured as follows. The subsequent section presents a summary of relevant literature and theories about the investment behavior of individual investors. The next section presents the research methodology and an examination of the data and the resultant findings, followed by concise summary and conclusions.

2. Literature Review and Theoretical Background

2.1 Overconfidence Bias

Kehneman and Tversky (1973) identified overconfidence as a psychological bias. Investors overestimate their stock knowledge and ignore investing risk. Barber and Odean (2013) suggested two overconfidence types. According to Deaves et al. (2009), overconfident investors trade excessively. Numerous research, including Özen and Ersoy (2019), Parveen et

al. (2021), Gavrilakis and Floros (2021), Quaicoe and Eleke- Aboagye (2021), Parhi and Pal (2021), and Chira et al. (2008), have examined the impact of overconfidence bias on investing

2.1.1 Demographics and Overconfidence Bias

Male investors are more subject to psychological prejudice than female investors (Baker et al., 2018; Adil, 2021; Coskun, 2016; Mushinada and Veluri, 2018). Barber and Odean (2001) found that men are more overconfident than women because they trade excessively and have poorer net profits. Unmarried investors are more subject to overconfidence bias (Coskun et al., 2016). Negative link between age and overconfidence. Teens are more prone to overconfidence and self-attribution bias, according to Mushinada and Veluri (2018). However, Prosad et al. (2015) demonstrated that gender, age, income, and trading experience significantly affect overconfidence bias among Delhi individual investors.

Additionally, overconfident investors invest in new companies with three years of growth and trade experience. Tekce and Yilmaz (2015) examined 305546 Turkish investors' investment behavior. They found that male investors are overconfident and that age positively affects overconfidence bias up to 30-34 but negatively affects older age groups. Investor experience is positively associated with overconfidence in low- value portfolios but adversely associated with high-value portfolios. Parhi and Pal (2021) found that wealthy people overreact to investment research and trading frequency. Investment experience boosts overconfidence bias (Beatrice et al., 2021 and Baker, 2018). They revealed that experienced investors are confident because they know the stock market, choose good stocks, and are responsible for their investments. In contrast, Raut and Kumar (2018) discovered that novice investors are prone to overconfidence, which is positively connected with education.

2.2 Representative Bias

Investors base judgments on pre-occupied information. Investors incorporate fresh ideas into current knowledge (Ritika and Kishore, 2020). Investors act irrationally in this bias because they base their decisions on a tiny sample. Chen et al. (2007), Alrabadi (2018), Rehan and Umer (2017), Sharma (2019), Waweru (2014), Girish and Sanningammanavara (2015), Kumara (2021), and Raut (2018) revealed a substantial relationship between representativeness and investment decisions.

2.2.1 Representativeness bias and Demographics

Demographics affect investors' biases (Oreng et al., 2021). Female investors have stronger representational bias (Choudhary et al., 2021). Representativeness bias is more common in younger investors. Education inversely affects representative bias. Graduates and postgraduates have less representativeness bias than high school graduates (Baker et al., 2019). Representational bias is more likely in less educated investors, according to Coskun et al. (2016). Nguyen and Schubler (2012) say education reduces representational bias. Retirees are more representativeness biased than private sector employees. Expert investors are similarly affected by representational prejudice, according to Baker et al. (2019).

2.3 Herding Bias

the influence of family, friends, and others on investors' investment decisions. Herding is when investors ignore their own information and expectations to follow others (Nofsinger and Sias, 1999). Raut et al. (2018), Quaicoe and Eleke-Aboagye (2021), and Jain (2019) found herding bias affects investing decisions.

2.3.1 Herding Bias and Demographics

Nair et al. (2017) found that male stock investors crowd less than females. Herding discrimination affects single investors more than married ones. Age and income strongly connect with herding bias. This bias is particularly prominent among older investors aged 51 to 60 who invest in new companies with quick growth and investors with less than a year or more than seven years of experience, according to Prosad et al. (2015). Investment experience decreases herding bias. Raut et al. (2020) and Raut and Kumar (2018) found that experienced investors ignore guidance. Less-experienced investors rely on peer decisions. Baker et al. (2019) discovered that public/private sector employees and retired investors exhibit a positive herding tendency, whereas self-employed investors do not. Beatrice et al. (2021) found that non-financial investors are more sensitive to herding bias than financial investors.

2.4 Availability Bias

It occurs when people estimate the likelihood of an event based on its recallability (Ritika and Kishor, 2020). Thus, investors estimate using
short-term events rather than long-term ones (Kehneman and Tversky, 1973). Alrabadi et al. (2018) and Khan et al. (2020) found availability bias strongly influenced investment decisions.

2.4.1 Demographics and Availability Bias

Few studies have examined how demographics affect availability bias. Choudhary and colleagues (2021) found that financial knowledge increases the risk of availability bias in investors. The cognitive bias encourages investors to overvalue information that is easily available, easy to recall, and similar to a future event (De Bondt et al., 2008). Experts in finance are more likely to use financial journals and newspapers (Van Rooij et al., 2011). Those with such attitudes are more likely to display availability bias because they focus on the latest stock information in newspapers and financial journals. All forms of biases affect investors with more than seven years of trading experience and significant trading volume (Prosad et al., 2015).

2.5 Anchoring Bias

investors base their decisions on a reference point, historical event, or trend, Jain et al. (2021). The Anchoring effect affects decision-making because investors are not objective about outcomes. People overestimate conjunctive event probability and underestimate disjunctive event probability due to the anchoring effect (Kahneman and Tversky, 1974). Soni and Desai (2019), Rehan and Umer (2017), Sharma (2019), Waweru et al. (2014), Girish and Sanningammanavara (2015), and Kumara et al. (2021) found a substantial anchoring bias-investment choice link.

2.5.1 Demographics and Anchoring Bias

Baker et al. (2019) found that anchoring bias affects younger investors more than older investors. Anchoring bias affects retirement investors and homemakers more than private sector workers. Experience is negatively correlated with anchoring bias since rookie investors assess by reference (Raut and Kumar, 2018). But Coskun et al. (2016) and Gupta and Ahmad (2016) found that anchoring bias is positively correlated with experience. Schooling reduces Anchoring Bias (Nguyen and Schubler, 2012). Anchoring prejudice affects women more than males. Lee et al. (2013) found that female participants are more likely to have an anchoring bias, which is negatively affected by money. Agnew (2006) found that higher-paid participants make better decisions.

2.6 Mental Accounting Bias

Individual investors organize, evaluate, and track financial actions using mental accounting. Individuals create separate accounts for their financial activity. Behavioral bias develops when people divide their money by source and goal (Angle et al., 2019).

2.6.1 Demographics and Mental Accounting Bias

Baker et al. (2018) found that Ph.D.-holding women and investors have reduced mental accounting bias. Experienced, higher-educated, and retired investors have less mental accounting bias. Rekik and Boujelbene (2013) noted that mental anchoring bias affects women more than men. Baker et al. (2019) evaluated investor occupation and mental accounting bias. Unemployed and retired investors are vulnerable to investment management issues. Beatrice et al. (2021) linked demographics to mental accounting bias. Income positively correlated with mental accounting bias, while gender did not. Education decreased mental accounting bias, according to Ozen and Ersoy (2019).

2.7 Loss Aversion Bias

Investors dread losses and weigh them more than wins due to the loss aversion bias (Tversky and Kahneman, 1991). This bias shows that investors are risk-averse and prefer to save. Investors care more about losses than wins and are less pleased with equal gains (Barberis and Thaler, 2003). following a loss, this bias makes investors risk-averse and causes them to sell their shares following a small price change and make irrational decisions. Bhosale (2020) and Chira et al. (2008) found that loss aversion bias strongly influences investing decisions.

2.7.1 Demographics and Loss Aversion Bias

Investors between 41 and 55 are more loss-averse than those between 25 and 40, according to Arora and Kumari (2015). Perhaps elderly folks have fewer years to recuperate from losses. They have low disposable income and must save for retirement, according to Johnson et al. (2006). Loss aversion in risky decisions increases with age, income, and wealth but decreases with education. The 41-55 age group regrets more than the 25-40 age group. Because of their loss aversion and remorse, elderly people invest less riskily. Females regret loss more than males. Also, women made fewer riskier financial decisions than men (Saivasan and Lokhande, 2022). Lee et al. (2013) found that women fear loss more than males.

Coskun et al. (2016) found that single investors fear losing more than married investors. Working-age investors have more loss aversion bias than retirees. Participants with less than five years of experience experienced increased loss aversion, according to Rekik and Boujelmene (2013).
Experienced investors have stronger loss aversion bias, according to Gupta and Ahmad (2016).

2.8 Disposition Bias

Shefrin and Statman (1985) said investors hold losses and sell winnings. Disposition effects start at different phases. Kahneman and Tversky's "editing" stage frames different possibilities, followed by the "evaluation stage," where investors follow the S-shaped evaluation function, which is concave in the gain zone and convex in the loss region. It displays risk-aversion in wins and risk-seeking in losses. Disposition bias significantly affects investment behavior, according to Chen et al. (2007), Sharma (2019), Girish and Sanningammanavara (2015), and Parveen (2021).

2.8.1 Disposition Bias and Demographics

Due to their investment confidence, Brown et al. (2006) discovered that male investors are less susceptible to the disposition effect than females. Kumar and Goyal (2015), Prasad et al. (2015), and Bouteska and Regaieg (2018) found that disposition impact affects 25-45-year-old investors more than older investors. But Beatrice et al. (2021) and Frino et al. (2015) found that older investors are risk-averse. Gong and Wright (2013) and Tekce et al. (2015) also claimed that disposition bias affects women, the elderly, and traders differently. Disposition bias affects high-income investors less (Isidore R. and P., 2019). Beatrice et al. (2021) confirm that income inversely affects position bias. Since they understand finance, high-income investors seek brokers for investment advice. Goo et al. (2010) discovered that higher-educated investors are less sensitive to disposition bias. Private sector employees are more subject to the disposition effect than self-employed people.

3. Research Methods

3.1 Questionnaire Design

The questionnaire pertains to matters related to the financial knowledge, demographic factors, and behavioral biases of individual investors in India. Academic experts assessed the survey instrument to ensure its validity. The study employs multiple metrics to assess the financial literacy of Indian stock investors (Mutlu and Ozer, 2021; Al-Tamimi and Bin Kalli, 2009; Ahmad et al., 2020; Adil et al., 2021). Multiple studies serve as the foundation for assessing the behavioral biases and investing decision-making of individual investors (Prosad et al., 2015; Jain et al., 2020; Ritika and Kishor, 2022; Baker et al., 2019; Menkhoff et al., 2006; Ahmad et al., 2017).

Questionnaires were considered the optimal tool for data collection in this scenario due to its flexibility, allowing respondents to complete them at their convenience, and the inability of researchers to influence their responses (Ahmad et al., 2020). Suresh (2021) argues that conducting a questionnaire survey can enhance data accuracy and reduce interviewer bias by

allowing respondents to answer the questionnaire according to their own judgment. The questionnaires consist of three sections (Raut, 2020; Kumara, 2021). The initial segment addresses inquiries regarding

the investor's demographic profile. The second component comprises inquiries pertaining to behavioral biases and investment choices, whereas the concluding section centers on financial literacy (Quddoos et al., 2020; Sabir et al., 2019; Lebdaoui et al., 2021).

3.2 Sample and Data Collection

The study focuses on individual investors in the Indian stock market as the target population. The study collected data from Maharashtra, Uttar Pradesh, and Gujarat because these three states have the biggest number of individual investors in India, according to BSE data.

The data collection for this study employed purposive and snowball sampling strategies (Sahi et al., 2013). The study employed these sample procedures due to the researcher's lack of access to the official database of investors. The participants for this study are chosen based on the following criteria –

1. The participants must be individuals who reside in the states of Maharashtra, Uttar Pradesh, and Gujarat.
2. The responders should have invested funds into stock market.

Around 600 individual investors who actively trade on NSE and BSE are contacted to participate in the survey for data collecting. The survey is conducted through both individual interviews and online platforms (Prosad et al., 2015a). A total of 515 questionnaires were returned by respondents out of the 600 distributed. In addition, out of the total of 515 questionnaires, 18 were excluded from the analysis due to inadequate and unfinished responses. A total of 515 questionnaires have been successfully completed, resulting in a response rate of 85.83 percent, making them appropriate for analysis.

4 Data Analysis

The research used several statistical methods, including one-way analysis of variance (ANOVA), factor analysis, paired t-test, independent sample t-test, and multiple regression analysis, to analyze the data. Eighteen univariate outliers were eliminated based on standard metrics before conducting these tests, yielding a final sample size of 497 respondents. To find univariate outliers, one must categorize items representing

separate variables and subsequently transform the data values of each observation into standardized scores, referred to as Z-Scores. The findings demonstrate that the standardized score of eighteen occasions surpasses the allowable range of ±3 (Hair et al., 2006). Eighteen cases were removed from further research as a result of this strategy during the univariate analysis.

4.1 Non Response Bias

Non-response bias poses a significant issue in survey research. The present study utilized a paired t-test to investigate non-response bias, specifically to ascertain whether statistically significant discrepancies existed between the responses of the initial 50 respondents and the final 50 respondents about ten behavioral biases. The paired t-test is utilized because of the continuous characteristics of the data and the normal distribution of the dependent variable. Table 4.1 demonstrates that there is no statistically significant difference between early and late responses regarding overconfidence (OC), representativeness (REP), herding (HRD), availability (AVL), mental accounting (MA), loss aversion (LA), disposition (DSP), financial literacy (FL), and investment decision-making (IDM), with the sole exception of anchoring (ANC). These findings mitigate concerns about non-response bias.

Table 4.1: Statistical test for non-response bias

		N	Correlation	Sig.
Pair 1	OC_E & OC_L	50	-.088	.543
Pair 2	REP_E & REP_L	50	-.048	.738
Pair 3	HRD_E & HRD_L	50	.087	.548
Pair 4	AVL_E & AVL_L	50	-.236	.099
Pair 5	ANC_E & ANC_L	50	-.317	.025
Pair 6	MA_E & MA_L	50	-.107	.458
Pair 7	LA_E & LA_L	50	-.185	.197
Pair 8	DSP_E & DSP_L	50	-.068	.640
Pair 9	FL_E & FL_L	50	.201	.162
Pair 10	IDM_E & IDM_L	50	.153	.287

Source: Researcher's Calculation

Notes: This table reports the results of Paired t-test for non-response bias, which compare the responses from the first and last 50 respondents on the following behavioral biases: OC, overconfidence; REP, representativeness; HRD, herding; AVL, availability bias; ANCH, anchoring bias; MA, mental accounting bias LA, loss aversion; DSP, disposition; FL, financial literacy and IDM, investment decision-making.

4.2 Assumption for Multiple Regression Analysis Normality of Data

The assessment of normality is carried out with the help skewness and kurtosis. The results depicts that Skewness and Kurtosis values are within the permissible range of -2 to +2 respectively (George & Mallery, 2010). Therefore, the data is normally distributed.

Homogeneity of Variance

Multiple regression analysis requires the assumption of homogeneity to be fulfilled (Field, 2006, Baker et al., 2019). Homogeneity of variance is calculated using Levene's Test. It is calculated on an interval scale across marital status. The results shown in Table 4.2 reveal that Levene values for each construct exceed the 0.05 significance level. Since, all values are not statistically significant across marital status, it implies equal amount of variance for each construct between married and unmarried factor. It confirms the notion of variance homogeneity.

Linearity of Data

In multiple regression analysis, the linearity of data was tested by examining the scatter plots (Hair et al., 2006). Linearity was tested to check the non-linear patterns in the data. This linearity assumption indicates that multivariate analysis techniques are valid in the present study.

Table 4.2: Levene's Test for Testing Homogeneity of Variance

	Levene Statistic	Sig.
OC	1.440	.231
REP	.056	.812
HRD	.373	.541
AVL	.310	.578
ANC	.106	.745
MTA	1.809	.179
LA	.914	.339
DSP	1.943	.164
FL	.110	.741
IDM	1.274	.260

Source: Researcher's Calculation

Multi collinearity of Variables

Multicollinearity, which exhibits varied correlation, is another multiple regression assumption. No variable correlates over 0.7 with another in Table A1, demonstrating no multicollinearity.

4.3 Demographics

The demographics of 497 responders are 81% male and 19% female. The gender gap among respondents is due to the fact that Indian families make investment decisions mostly by men. Since men make most investment decisions in India, there are fewer female responses. The largest percentage of the sample is 26–35 years old (62.5 percent) and 36–45 years old

(24.33%). The majority of participants earn 50000 to 100000 rupees per month (56.34%) and 20000 to 50000 rupees (23.34%). 27.5 percent have graduate degrees, 47.7 percent postgraduate degrees, and 23

percent professional certificates. The percentage of married and unmarried respondents is same. 61% work in the public or private sector. 57.14 percent have 2–5 years of investment experience. Additionally, 61.97 percent of responders are non-financial.

4.4 Factor Analysis

Factor analysis examines the structure of behavioral bias, financial literacy, and investment decision-making assessment questions. Principal component analysis (PCA) with varimax rotation extracts. Norman (2010) extensively examined multivariate analysis assumptions, including normality and Likert-type scale data as continuous for parametric testing. Therefore, PCA is suitable for this study. The Kaiser-Meyer-Olkin sample adequacy measure is 0.854, meeting exploratory factor analysis requirements. Ten components had eigenvalues > one, accounting for 68.35% of variation. Hair et al. (2006) explored rotational factor loading limits over 0.5. Ten factors were identified: overconfidence, representativeness, herding, availability, anchoring, mental accounting, loss aversion, disposition bias, financial literacy, and investment decision- making.

4.5 Reliability

Variable reliability is assessed using Cronbach's alpha. It measures correlation between variables. On a scale, it rates item reliability. A scale is adequate if its Cronbach's alpha surpasses 0.70, according Sekaran (2000). Cronbach's alpha coefficients for each factor are in Table A2. Each factor's Cronbach's alpha exceeds 0.70. This suggests good internal consistency among measured variables within each factor. It shows strong correlations between all variables inside each factor (Hair et al., 2006). The item-to-total correlation and inter-item correlation were used to determine variable reliability and internal consistency. The table shows that item-to-total correlation exceeds 0.5. This suggests that component measurement items share a lot of variance. The inter-item correlation coefficients for each item exceed the allowed limit of 0.3, indicating a greater association between questions that assess the same construct (Robinson et al., 1991).

Cronbach's alpha and inter-item correlation show factor variables' internal consistency.

4.6 Behavior bias rankings

The mean score of 497 respondents' responses to questions within the same topic was calculated to examine behavioral biases. Table 4.3 assesses individual investor behavioral biases according to prevalence. The mean loss aversion score exceeds three, showing that it strongly affects Indian individual investors' investing decisions. Average loss aversion, mental accounting, and representativeness scores are 3.14, 2.96, and 2.92. Herding, overconfidence, and disposition bias have the lowest average scores, indicating that most respondents are not prone to them.

Table 4.3: Ranking of behavioral biases

Behavioral biases	Mean	Rank
Overconfidence	2.767	7
Representativeness	2.92	3
Herding	2.69	8
Availability	2.79	5
Anchoring	2.83	4
Mental Accounting	2.96	2
Loss Aversion	3.14	1
Disposition	2.774	6

Source: Researcher's Calculation

Note: The table ranks the behavioral biases based on the mean score for 497 respondents.

4.7 Demographic variables and behavioral biases

Assessing the differences in behavioral biases across demographic variables requires the application of an independent t-test and ANOVA. Table 4.4 The independent t-Test is utilized to compare the means of two distinct groups based on gender, marital status, and career sector in relation to behavioral biases. A t-Test was utilized due to the continuous nature of the dependent variable and the categorical character

of the independent variable. An independent sample t-test was conducted to determine if there is a statistically significant difference in the average score between two distinct groups based on gender, marital status, and occupation sector. These groups exhibit notable variations in their behavioral biases.

Table 4.4: Behavioral biases across gender, marital status, and occupation sector of individual investor

	t- Test for Gender				t- Test for Marital status				t- Test for Occupational Sector			
Variables	**Levene's tes**	**t-Value**	**Significance (2-tailed)**	**Mean difference**	**Levene's tes**	**t-Value**	**Significance (2-tailed)**	**Mean difference**	**Levene's tes**	**t-Value**	**Significance (2-**	**Mean difference**

	t				t				t		tailed)	e
Overconfidence	0.236	0.692	0.489	0.050	1.440	-0.262	0.793	-0.015	0.145	-0.582	0.561	-0.053
Representativenes s	0.192	-0.436	0.663	-0.050	0.056	-0.510	0.610	-0.0325	0.193	0.065	0.948	0.005
Herding	1.854	1.907	0.057	0.144	0.373	1.322	0.187	0.0787	6.401	0.428	0.669	0.039
Availability	5.362	-0.367	0.714	-0.025	0.310	2.748	0.006	0.147	5.476	0.296	0.767	0.027
Anchoring	1.562	-2.135	0.033	-0.15	0.106	-0.301	0.764	-0.017	0.422	0.414	0.679	0.038
Mental Accounting	1.381	-0.801	0.424	-0.06	1.809	1.215	0.225	0.069	0.696	-0.952	0.342	-0.087
Loss Aversion	0.138	0.788	0.431	0.057	0.914	-1.209	0.227	-0.068	0.132	0.490	0.624	0.045
Disposition	0.065	0.753	0.452	0.0494	1.943	-0.530	0.597	-0.027	0.838	1.130	0.259	0.104
Financial Literacy	0.193	-0.435	0.664	-0.03	0.110	-0.484	0.629	-0.026	0.066	0.581	0.562	0.053

Source : Researcher's Compilation

Note- This table shows the mean difference in behavioral biases for gender, marital status and occupation sector. The numbers in italics show significance at the 0.05 level or higher

The mean scores of different groups show that males are more susceptible to overconfidence, herding behavior, loss aversion, and disposition bias. Representativeness, availability,

anchoring, and mental accounting bias affect women more. The mean financial literacy score shows that women are more financially literate than men.

In Table 4.4, males and females had significantly different anchoring bias values, with a significance threshold of 0.05. Table 4.4 shows that males anchor prejudice more than females, as shown by the mean difference. At 0.05 significance level, Table 4.4 shows a difference in availability bias between married and unmarried people. Table 4.4 shows that unmarried men are more susceptible to availability bias than women (mean difference = 0.147).
Financial and non-financial industries showed no statistically significant bias difference (Table 4.4). This suggests that investors' behavioral biases are unaffected by their occupation.
Table 4.5 uses the ANOVA test to compare the means of three or more independent groups to find significant differences. This examination analyzes numerous category data groups to evaluate behavioral biases. Significant differences ($p< 0.05$) occur in average scores among age groups for overconfidence bias, anchoring, mental accounting, loss aversion biases, and financial literacy. Socioeconomic groups differ significantly ($p< 0.05$) in the existence of representativeness, anchoring, and loss aversion biases. Financial literacy varies greatly by income. The study found no significant difference ($p>0.05$) in behavioral biases and financial literacy across educational categories. Except for the overconfidence bias, Table 4.5 shows no statistically significant changes in biases between occupational categories. It shows that investment experience affects overconfidence, representativeness, and financial literacy. Additionally, those with over 10 years of experience had the highest average ratings for overconfidence and anchoring.

Table 4.5: ANOVA for demographic variables and behavioral biases

Variables	**Age**			**Income**			**Education**			**Occupation**			**Experience**		
Between Groups	**Mean Square**	**F**	**P value**	**Mean Square**	**F**	**P value**	**Mean Square**	**F**	**P value**	**Mean Square**	**F**	**P value**	**Mean Square**	**F**	**P value**
Overconfidence	3.019	3.082	**0.009**	1.826	1.842	0.103	0.977	0.98	0.420	3.399	3.466	**0.008**	6.200	6.403	**<.001**
Representativeness	0.774	0.772	0.570	2.426	2.462	**0.032**	1.915	1.93	0.104	2.081	2.099	0.080	1.674	1.680	0.170
Herding	0.424	0.421	0.834	0.572	0.570	0.723	1.659	1.67	0.156	1.266	1.268	0.281	0.125	0.124	0.946
Availability	0.831	0.829	0.529	0.123	0.122	0.987	1.358	1.36	0.246	1.303	1.306	0.267	0.615	0.613	0.607
Anchoring	2.224	2.252	**0.048**	2.578	2.620	**0.024**	0.948	0.95	0.436	0.998	0.998	0.408	2.738	2.767	**0.041**

Mental Accounting	2.283	2.313	**0.043**	0.723	0.721	0.608	1.139	1.14	0.337	1.612	1.620	0.168	2.239	2.256	0.081
Loss Aversion	3.026	3.090	**0.009**	1.517	1.525	0.18	0.872	0.87	0.481	0.693	0.691	0.599	1.603	1.609	0.186
Disposition	0.564	0.561	0.730	1.645	1.656	0.144	1.358	1.36	0.246	1.987	2.003	0.093	0.527	0.526	0.665
Financial Literacy	2.711	2.759	**0.018**	4.934	5.140	**<.001**	0.342	0.340	0.851	0.717	0.715	0.582	3.149	3.191	**0.023**

Source : Reseacher's Compilation

Note- This table reports the results of one-way ANOVA for behavioral biases across demographic characteristics: age, education, occupation, income and investment experience. The numbers in italics show significance at the 0.05 level or higher

4.2.5 How are demographic factors and financial literacy related to the behavioral biases

Demographic variables are assessed using ordinal and nominal scales. Instead, behavior and financial literacy biases were measured continuously. The table shows variable correlation for multicollinearity analysis. Multicollinearity limits regression coefficients and makes it harder to evaluate their effects. Tabachnick and Fidell (2007) suggested deleting an interrelated component to improve prediction. No variable has a correlation coefficient greater than 0.70, reducing multicollinearity.

Figures 4.6 and 4.7 show the results of a multiple regression analysis of eight behavioral biases and financial literacy. Financial literacy and demographic parameters including Age, Income, Occupation, Investment experience, Gender, Marital status, Occupation sector, and Education are analyzed. The coefficient compares each group's impact on the control group. Respondents aged 18–25 are the age reference group. The reference group for monthly income is those earning under $20,000. Full-time workers are the reference group. The reference group has fewer than two years of financial experience. Male respondents form the reference group. Unmarried respondents are the marital status reference group. In education, the reference group is elementary school graduates. All replies with 10+2 qualifications will be included.

Multiple regression analysis considered the mean score. Scatter plots tested data linearity (Hair et al., 2006). Data linearity was examined to detect non-linear tendencies. The assumption of linearity supports this study's multivariate analytic methods.

Table 4.6: Regression analysis on behavioral biases across financial literacy and demographic variables

	Model 1	Model 2	Model 3	Model 4	Model5
	Overconfidenc	Representativenes	Herdin	Availabilit	Anchorin

	e		s		g		y		g	
	B	P	B	P	B	P	B	P	B	P
(Constant)	0.018	0.972	-0.66	0.2	-0.203	0.711	-0.306	0.573	0.251	0.631
Age (18-25=0)										
25-35	-0.116	0.185	0.03	0.726	0.04	0.662	-0.018	0.84	-0.135	0.121
35-45	-0.113	0.207	0.039	0.657	0.031	0.737	-0.023	0.808	-0.081	0.366
45-55	0.206	0.037	0.056	0.561	-0.026	0.8	0.12	0.241	-0.01	0.916
55 above	-0.329	0.002	-0.057	0.595	0.005	0.968	-0.091	0.416	-0.133	0.216
Income (Below 20000=0)										
20000-50000	0.042	0.742	-0.168	0.182	0.146	0.274	-0.01	0.943	-0.09	0.478
50000-100000	-0.05	0.734	-0.165	0.257	0.149	0.336	0.035	0.817	-0.173	0.24
100000-200000	0.033	0.775	-0.207	0.071	0.094	0.44	0.042	0.729	-0.141	0.223
200000-500000	-0.022	0.71	-0.026	0.653	0.028	0.651	-0.02	0.745	-0.026	0.652
above 500000	-0.028	0.551	0.028	0.541	-0.008	0.877	-0.025	0.617	0.058	0.222
Occupation (Full Employment =0)										

Retirement	0.012	0.802	0.122	0.012	0.069	0.177	0.11	0.032	-0.033	0.506
self-employed	-0.013	0.798	0.008	0.867	0.039	0.468	0.079	0.134	-0.005	0.919
Own company	0.117	0.015	-0.015	0.747	0.084	0.093	0.002	0.968	-0.03	0.528
Other	0.015	0.751	0.076	0.112	-0.035	0.486	0.056	0.265	0.022	0.656
Experience (Less Than 2 yrs= 0)										
2-5yrs	-0.023	0.701	0.028	0.642	-0.024	0.708	-0.051	0.422	0.004	0.943
5-10yrs	0.07	0.261	0.094	0.125	-0.031	0.634	-0.026	0.689	0.053	0.396
above 10	0.167	<.001	0.045	0.365	-0.023	0.66	0.035	0.498	0.128	0.011
Gender (Male=0)										
Female	-0.044	0.363	-0.007	0.882	-0.093	0.067	-0.004	0.944	0.077	0.112
Marital Status (Single=0)										
Married	-0.004	0.941	-0.015	0.776	-0.053	0.338	-0.138	0.012	0.018	0.726
Occ Sector (Financial= 0)										
Non-financial	0.002	0.974	0.058	0.268	0.023	0.683	0.016	0.777	-0.016	0.767
Education (10+2 =0)										
Grad					-	0.84				

	0.094	0.604	0.301	0.092	0.037	5	0.118	0.533	0.054	0.764
post grad	0.156	0.449	0.435	0.032	-0.09	0.677	0.218	0.308	0.168	0.414
Doctoral	0.073	0.176	0.077	0.143	-0.01	0.857	0.135	0.016	-0.004	0.943
Professional	0.047	0.795	0.376	0.034	0.067	0.723	0.2	0.285	0.065	0.717
Financial Literacy	0.166	<.001	0.294	<.001	-0.039	0.415	0.076	0.105	0.236	<.001
R2	0.128		0.157		0.046		0.058		0.09	
F	2.869		3.661		0.943		1.217		3.036	

Note- N= 497. This table reports the results of linear regression on behavioral biases across financial literacy and demographic characteristics. The numbers in italics show significance at the 0.05 level or higher. β, unstandardized coefficient; p, significance value; gender, age, marital status, education, occupation, income and investment experience converted into dummy variables.

4.2.5.1 Model 1: How demographic variables and financial literacy relate to overconfidence bias

Table 4.6 indicates that Model 1 is statistically significant (F= 2.86, p<.001). The dependent variable is overconfidence (OC), while all demographic characteristics and financial literacy serve as independent factors. The explanatory capacity of model 1 is 12.8 percent, as indicated by the R2 value of 0.128. This table also demonstrates that age, occupation, experience, and financial literacy are statistically significant. Investors aged 45 to 55 exhibit a higher propensity for overconfidence bias compared to those aged 18 to 25, whereas individuals aged 55 and above demonstrate lower levels of overconfidence than the 18 to 25 age group. Investors who own their own companies exhibit greater overconfidence than those who are fully employed (either privately or publicly). Overconfidence correlates positively with investment experience. Investors with over 10 years of experience exhibit greater overconfidence than those with less than two years of experience. Financial literacy exhibits a statistically significant positive correlation with overconfidence. Financial knowledge enhances the overconfidence bias among investors.

4.2.5.2 Model 2: How demographic variables and financial literacy relate to representativeness bias

Table 4.6 indicates that regression model 2 is statistically significant (F= 3.66, p<.001). In this model, the dependent variable is representativeness bias, whereas the independent variables consist of demographic factors and financial literacy. The explanatory power of this model is 15.7 percent, as the R^2 value equals 0.157. The results reveal that the coefficients of financial literacy and demographic factors (occupation and education) are statistically significant. Financial literacy is positively correlated with representativeness bias. An enhancement in financial literacy correlates with an escalation in representative bias among investors.

Moreover, the coefficient for one income category (i.e., 1,000,000 to 2,000,000) is negative and statistically significant at the 0.10 level. Individuals within the income bracket of 100,000 to 200,000 have a lesser degree of representational bias compared to those from lower-income groups. Retired investors exhibit a favorable and substantial relationship (p<.05) with representational bias compared to fully working persons. The coefficients for various educational categories are statistically significant at the 0.05 level. Investors with higher educational attainment exhibit a greater tendency towards representativeness bias compared to those with only a basic education.

4.2.5.3 Model 3: How demographic variables and financial literacy relate to herding bias
The findings demonstrate that regression model 3 for herding bias lacks statistical significance (F = .943, p > .05). The dependent variable in this regression model is herding bias. The independent variables consist of demographic factors and financial literacy. The results indicate that the predictor variables fail to account for the variance in this model. The R2 score (.046) was statistically insignificant as well. Herding bias is unaffected by demographic variables and financial literacy.

4.2.5.4 Model 4: How demographic variables and financial literacy relate to availability bias
The findings demonstrate that regression model 4 for availability bias lacks statistical significance (F= 1.217, p>.05). The results indicate that the predictor variables fail to account for the variance in this model. The R2 score (.058) was statistically insignificant as well. Availability bias is unaffected by demographic characteristics and financial literacy.
4.2.5.5 Model 5: How demographic variables and financial literacy relate to anchoring bias

The findings demonstrate that regression model 5 for anchoring bias is statistically significant (F= 3.036, p<.001). This regression model accounts for merely 9 percent of the variation, since the R^2 value is 0.09. The dependent variable in this model is anchoring bias, whereas demographic characteristics and financial literacy serve as independent variables. The model determined that the coefficients for one category of investment experience (i.e., over 10 years) and financial literacy are statistically significant. Investors with over a decade of financial expertise have a more pronounced influence of anchoring bias compared to their less experienced counterparts. Moreover, financial literacy exhibits a substantial positive correlation (p<.001) with anchoring bias. Financial knowledge amplifies the influence of anchoring bias among investors.

4.2.5.6 Model 6: How demographic variables and financial literacy relate to mental accounting bias

The findings demonstrate that regression model 6 for mental accounting bias is statistically significant (F= 2.783, p<.001). The model explains
12.4 percent of the variance (R^2 = 0.124). In regression model 6, the dependent variable is mental accounting, whereas the independent variables are demographic factors and financial literacy. The model demonstrates a statistical correlation between demographic characteristics (experience, marital status, and occupational sector) and financial literacy with mental accounting bias. Investors with 5 to 10 years of investment expertise had a more pronounced effect of mental accounting bias compared to their less experienced counterparts. Married investors experience a diminished influence of mental accounting bias compared to unmarried investors. Investors in the non-financial sector exert a more significant influence on mental accounting than those in the financial sector. Furthermore, financial literacy enhances mental accounting bias. Financially literate investors are influenced by mental accounting bias.

Table 4.7: Regression analysis on behavioral biases across financial literacy and demographic variables (continued)

	Model 6		Model 7		Model 8		Model 9	
	Mental Accounting		Loss Aversion		Disposition		Financial Literacy	
	B	P	B	P	B	P	B	P
(Constant)	-0.17	0.746	0.222	0.677	0.212	0.695	0.843	0.112
Age (18-25=0)								
25-35	-0.037	0.67	-0.166	0.062	-0.109	0.226	-0.179	0.043
35-45	0	0.997	-0.113	0.215	-0.068	0.459	-0.062	0.491
45-55	0.135	0.17	0.258	0.01	-0.037	0.716	0.243	0.014
55 above	-0.135	0.214	-0.347	0.002	-0.032	0.777	-0.305	0.005
Income (Below 20000=0)								

20000-50000	0.023	0.856	-0.081	0.535	-0.131	0.323	-0.406	0.002
50000-100000	-0.065	0.661	-0.022	0.882	-0.032	0.832	-0.461	0.002
100000-200000	-0.057	0.626	-0.061	0.606	-0.061	0.611	-0.369	0.002
200000-500000	-0.092	0.115	-0.114	0.056	-0.075	0.216	0.011	0.859
above 500000	-0.015	0.745	0.01	0.84	-0.059	0.225	0.038	0.425
Occupation (Full Employment =0)								
Retirement	-0.024	0.627	0.062	0.215	0.115	0.024	0.066	0.183
self-employed	-0.086	0.093	0.105	0.043	0.049	0.353	0.067	0.191
Own company	0.032	0.499	0.024	0.626	0.011	0.82	-0.032	0.506
Other	0.023	0.636	-0.003	0.956	-0.032	0.527	0.016	0.753
Experience (Less Than 2 yrs= 0)								
2-5yrs	0.017	0.781	0.022	0.727	0.039	0.535	0.052	0.397
5-10yrs	0.153	0.015	0.075	0.24	-0.006	0.924	0.063	0.318
above 10	0.07	0.163	0.069	0.176	0.036	0.487	0.139	0.006
Gender (Male=0)								
Female	0.019	0.694	-0.027	0.584	-0.03	0.545	0.014	0.77
Marital Status (Single=0)								
Married	-0.103	0.05	0.041	0.438	0.011	0.837	-0.029	0.586

Occ Sector (Financial=0)								
Non-financial	0.108	0.044	0	0.995	-0.031	0.573	0.01	0.857
Education (10+2 =0)								
Grad	0.044	0.808	-0.078	0.672	-0.015	0.935	0.015	0.934

Note- N= 497. This table reports the results of linear regression on behavioral biases across financial literacy and demographic characteristics. The numbers in italics show significance at the 0.05 level or higher. β, unstandardized coefficient; p, significance value; gender, age, marital status, education, occupation, income and investment experience converted into dummy variables.

4.2.5.7 Model 7: How demographic variables and financial literacy relate to loss aversion bias
The findings indicate that regression model 7 is statistically significant (F= 2.121, p<.01). This model's explanatory power is merely 9.8 percent. This model incorporates loss aversion as the dependent variable. Demographic characteristics and financial literacy serve as the independent variable. Model 7 determined that demographic characteristics (age, income, employment) and financial literacy strongly influence investors' loss aversion bias. Table 4.20 indicates that loss aversion bias influences the 25 to 35-year age group more than the 18 to 25-year age group at the
0.10 significance level.
Conversely, investors aged 45 to 55 exhibit a more pronounced effect of loss aversion compared to those in the 18 to 25 age group, at a significance level of 0.01. Investors aged 55 and older exhibit a diminished propensity for loss aversion bias. One income category (i.e., 200,000

to 500,000) is negative and statistically significant at the 0.10 level. Self-employed individuals exhibit more loss aversion than those in the reference group. Financial literacy exhibits a positive correlation with loss aversion bias.
4.2.5.8 Model 8: How demographic variables and financial literacy relate to disposition bias

Model 8 illustrates the correlation between the dependent variable (disposition bias) and the independent variables (demographic factors and financial knowledge). The findings indicate that regression model 8 is statistically insignificant (F= 1.456, p>.05). The model's explanatory power is merely 6.9 percent. The results indicate that the predictor variable does not account for the variation in this model.
4.2.5.9 Model 9: How demographic variables relate to financial literacy

The findings demonstrate that regression model 9 is statistically significant (F=2.265, p<.001). The model's explanatory power is 9.9 percent. In regression model 9, the dependent variable is

financial literacy, while the independent variable comprises demographic characteristics. The table indicates a statistical correlation between financial literacy and demographic characteristics, specifically Age, Income, and Experience. The findings indicate that investors aged 25-35 and older exhibit worse financial literacy compared to those aged 18-25. Investors aged 45 to 55 exhibit more financial literacy than those in the reference category. The findings indicate that income is inversely correlated with financial knowledge. It signifies that financial literacy diminishes as money escalates. Investment experience significantly enhances financial literacy at the
0.01 level. Table 4.20 indicates that individuals with over ten years of investment experience exhibit greater financial literacy compared to those with limited investment experience.
Discussions and Conclusions

This study analyzes how investor demographics and financial literacy affect behavioral biases and investing decisions. Investors receive demographically tailored information from this research. Individual investors' main behavioral biases are loss aversion, mental accounting, and representativeness. Demographics, financial literacy, behavioral biases, and investment decision-making are examined using t-Test, one-way ANOVA, and multiple regression models.
Multiple regression analysis shows that demographic factors and financial literacy affect overconfidence, representativeness, anchoring, mental accounting, loss aversion, and disposition bias. Demographic factors and financial expertise do not alter herding or availability biases.

The study found that age, occupation, investment experience, and financial literacy were the main demographic characteristics influencing investor behavior.
The study data showed that investor age significantly affected overconfidence bias and loss aversion. The study shows that overconfidence bias increases between 45 and 55 and then declines. It implies that overconfidence declines with age. These findings match Tekce and Yilmaz (2015) and Tehrani and Gharehkoolchian (2012). Middle-aged investors are less affected by loss aversion than young and elderly investors. These data support Arora and Kumari (2015) and Johnson et al. (2006) but contradict Ates et al. (2016).
Income negatively affects loss aversion bias and representativeness heuristic, according to study. Rich people are less susceptible to representational and loss aversion biases. These findings support Isidore R. and P. (2019) but contradict Saxena (2020).

Investment experience strongly impacts overconfidence, anchoring, and mental accounting biases. Investment experience exacerbates behavioral biases. Experienced investors benefit from overconfidence. Bhandari and Deaves (2006), Deaves et al. (2010), Prosad et al. (2015), and Beatrice et al. (2021) show that experienced investors are more susceptible to overconfidence bias. Experienced investors are confident due to their stock market knowledge, superior stock selection, and full responsibility for investment results. Raut and Kumar (2018) dispute this study's findings.

Investment experience positively correlates with mental accounting and anchoring bias. This supports Ates et al. (2016) and Gupta and Ahmad (2016) but contradicts Baker (2018).
Current research shows that company-owning investors are more prone to overconfidence bias than fully employed investors. Retirement investors evaluate stocks based on past performance and are biased by representativeness. Self-employed investors are more loss-averse. Representational bias inversely correlates with investor education. Graduate and postgraduate investors are less susceptible to representational bias than their less educated peers, according to Nguyen and Schubler (2012), Baker et al. (2018), and Ates (2016).
Financial knowledge and investor demographics appear to influence behavioral biases and investment decisions. Financial literacy positively affects overconfidence, representativeness, anchoring, mental accounting, and loss aversion. It's also crucial to investing decisions. These findings match Ates et al. (2016), Owusu and Laryea (2022), and Baker (2018). For loss aversion, Rasool and Ullah (2019) found contradicting results, but Ates et al. (2016) did for overconfidence. Financial literacy increases investor bias.

Indian investors' financial literacy is influenced by demographics. Investor financial literacy depends on age, income, and experience. Investors aged 25-35 and older had lower financial literacy than 18-25-year-olds, but those aged 45-55 have higher literacy. Financial literacy is adversely correlated with income, but positively correlated with investment experience.
Results show that married investors are less susceptible to mental accounting bias than unmarried ones. The data show that gender does not alter Indian investors' behavioral biases. Non-financial investors are more susceptible to behavioral biases.
This study also contributes to the prospect theory. Prospect theory emphasis that investors do not behave rationally contrary to expected utility theory. Here, in this study , it was found that investment decisions are affected demographic factors, this shows that investors do no behave rationally and are affected by bahavioural biases and demographic factors.
Analyzing how demographics and financial literacy affect individual investor decision-making has various practical ramifications. Financial firms can customize investment products and educational materials by understanding demographic data like age, income, education, and occupation. Second, examining the relationship between financial literacy and investing decisions may help governments create targeted financial education initiatives. These exercises may teach investment principles, risk management, and long-term financial planning.
Recognizing how demographics affect investment behavior could help financial advisors adapt advice. Based on clients' demographics and financial knowledge, they can change communication techniques and offer investment programs. Businesses can also boost investment product marketing with demographic and financial literacy data. This research can improve financial services, help investors make better decisions, and improve financial well-being. Future study for further researches should identify the impact of social factors in developing countries since in developing nations every individual is socially linked with eachother and their behaviour is affected by them.

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Appendix

Table A1: Correlation Matrix for testing multicollinearity

Correlation	**Gender**	**Mar_status**	**Age**	**Income**	**Education**	**Occupation**	**Invt_exp**	**Occ_Sector**	**DSP**	**LA**	**MA**	**ANC**	**AVL**	**HRD**	**REP**	**OC**	**FL**	**IDM**
Gender	1																	
Mar_status	-0.038	1																
Age	-.122**	.518**	1															

Income	-.124**	.183**	.282**	1														
Education	.178**	-0.018	-0.036	-.277**	1													
Occupation	-0.075	-0.014	-0.033	-.107*	-.336**	1												
Invt_exp	-.218**	.364**	.493**	.391**	.102*	-0.027	1											
Occ_Sector	-.115*	0.066	0.065	-.198**	-.510**	.243**	-0.060	1										
DSP	-0.034	0.024	0.036	0.027	0.051	-0.014	0.041	-0.051	1									
LA	-0.035	0.054	0.015	0.014	0.055	0.048	.094*	-0.022	.158**	1								
MA	0.036	-0.055	-0.008	-0.073	0.055	-0.022	0.077	0.043	0.044	.186**	1							
ANC	.096*	0.014	-0.035	-0.045	0.010	0.031	0.034	-0.019	0.085	.169**	.103*	1						
AVL	0.016	-.123**	-0.032	-0.010	0.046	0.059	-0.022	-0.013	.143**	.259**	.223**	.103*	1					
HRD	-0.085	-0.059	-0.034	0.011	0.059	0.005	-0.021	-0.019	.213**	.119**	0.044	0.018	.150**	1				
REP	0.020	0.023	0.052	-0.014	0.066	0.038	.093*	-0.003	.225**	.299**	.159**	.269**	.171**	-0.033	1			
OC	-0.031	0.012	-0.030	-0.028	-0.054	0.066	.091*	0.026	0.022	.204**	.268**	.177**	0.028	-0.061	0.046	1		
FL	0.020	0.022	0.039	0.017	0.041	0.073	.094*	-0.026	.151*	.195*	.241*	.281*	0.08	-	.330*	.197*	1	

									*	*	*	*	7	0.054	*	*		
IDM	0.082	0.029	-0.009	-0.008	.104*	0.057	0.030	0.025	.141**	.201**	.134**	.220**	.129**	0.030	.213**	.131**	.305**	1

Note- This table reports the correlation between variables, which provides a means of determining multicollinearity. *,**Significant at 0.05 and
0.01 levels (two-tailed), respectively

Table A2: Reliability assessment of research Instruments

Item	**Mean**	**SD**	**Cronbach's α**	**Inter-item Correlation**	**Corrected item-total Correlation**
OC1	2.71	.872	.886	.45-.62	.717
OC2	2.83	.777			.673
OC3	2.72	.824			.722
OC4	2.74	.800			.669
OC5	2.79	.821			.691
OC6	2.77	.845			.721
REP1	2.94	.898	.904	.57-.69	.781
REP2	2.97	.925			.759
REP3	2.95	.934			.745
REP4	2.96	.881			.736
REP5	2.97	.885			.782
HRD1	2.85	.873	.886	.52-.67	.746
HRD2	2.86	.857			.698
HRD3	2.86	.870			.717
HRD4	2.86	.856			.704
HRD5	2.87	.879			.755

AVL1	3.00	.827	.895	.53-.64	.718
AVL2	3.00	.860			.722
AVL3	2.98	.824			.702
AVL4	2.97	.837			.724
AVL5	2.97	.836			.719
AVL6	2.99	.819			.726
ANC1	2.97	.835	.885	.51-.66	.729
ANC2	3.05	.816			.692
ANC3	3.06	.847			.730
ANC4	3.05	.854			.720
ANC5	3.02	.860			.738
MTA1	2.98	.840	.895	.50-.65	.744
MTA2	2.91	.816			.703
MTA3	2.95	.847			.717
MTA4	2.94	.839			.717
MTA5	2.93	.783			.683
MTA6	2.92	.800			.739
LA1	3.03	.831	.909	.50-.65	.757
LA2	3.08	.823			.704
LA3	2.99	.807			.717
LA4	3.11	.792			.714
LA5	3.06	.790			.711
LA6	3.05	.829			.737
LA7	3.06	.823			.747

DSP1	2.95	.790	.813	.56-.62	.683
DSP2	3.02	.785			.637
DSP3	3.04	.778			.671
IDM1	3.00	.957	.895	.64-.71	.770
IDM2	2.98	.935			.753
IDM3	2.97	.932			.769
IDM4	2.94	.843			.785
FL1	3.02	.841	.891	.47-.67	.717
FL2	3.03	.828			.705
FL3	3.04	.820			.712
FL4	3.08	.819			.694
FL5	3.07	.810			.701
FL6	3.05	.830			.721

Source: Researcher's Compilation

Note: OC, overconfidence; REP, representativeness; HRD, herding; AVL, availability; ANC, anchoring; MTA, mental accounting; LA, loss aversion; DSP, disposition bias; IDM, investment decision making; FL, financial literacy; SD, standard deviation. Cronbach's α coefficient > 0.7 indicates reliable data.