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Does a behavioural bias affect personality traits and investors' sentiments? : Smart PLS Model

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هل يؤثر التحيز السلوكي على سمات الشخصية ومشاعر المستثمرين؟ : نموذج *Smart PLS*

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Abstract:
This study investigates the influence of behavioral biases on personality traits and investors' sentiments, focusing on overconfidence, disposition effect, anchoring, representativeness, mental accounting, emotional bias, and herding biases. Data from 753 respondents across Gujarat's municipal corporation cities were analyzed using a Smart PLS model and structural equation modeling (SEM). Findings indicate that these biases significantly impact investors' sentiments, with some biases, like overconfidence and disposition effect, negatively affecting sentiments, while others, like mental accounting and emotional bias, have a positive impact. Additionally, personality traits such as extraversion and openness positively influence sentiments, whereas neuroticism has a negative effect. Limitations include the sample size and reliance on self-reported data, and the study's originality lies in its exploration of these relationships comprehensively. Practical implications suggest investors, advisors, and policymakers can benefit from understanding these dynamics to make more informed investment decisions and promote financial literacy. Overall, this research contributes to the understanding of how biases and personality traits shape investors' sentiments, aiding in the development of strategies to mitigate irrational decision-making in financial markets.

Keywords: Anchoring Biases, Disposition biases, Mental Accounting, Overconfidence, Representativeness.

الملخص
تبحث هذه الدراسة في تأثير التحيزات السلوكية والسمات الشخصية على مشاعر المستثمرين، مع التركيز على التحيزات مثل الثقة الزائدة، وتأثير التصرّف، والتثبيت، والتمثيلية، والمحاسبة الذهنية، والانحياز العاطفي، والانقياد الجماعي. تم تحليل بيانات 753 مشاركاً من مدن ولاية غوجارات باستخدام نموذج Smart PLS ونمذجة المعادلات الهيكلية (SEM). تكشف النتائج أن هذه التحيزات تؤثر بشكل كبير على مشاعر المستثمرين، حيث أن بعض التحيزات، مثل الثقة الزائدة وتأثير التصرّف، تؤثر سلبًا على المشاعر، في حين أن التحيزات الأخرى، مثل المحاسبة الذهنية والانحياز العاطفي، لها تأثير إيجابي. علاوة على ذلك، تؤثر السمات الشخصية مثل الانبساط والانفتاح بشكل إيجابي على مشاعر المستثمرين، بينما يكون

لسمّة العصابية تأثير سلبي. تشمل القيود الرئيسية للدراسة حجم العينة والاعتماد على البيانات المبلغ عنها ذاتيًا. وتكمن أصالة الدراسة في استكشاف هذه العلاقات بشكل شامل. تقدم النتائج دلالات عملية للمستثمرين والمستشارين وصانعي السياسات من خلال تعزيز الثقافة المالية والمساعدة في تطوير استراتيجيات للحد من القرارات غير العقلانية في الأسواق المالية. تسهم هذه الدراسة في فهم أعمق للعوامل النفسية التي تشكل سلوك المستثمرين.

الكلمات المفتاحية: التمويل السلوكي، معنويات المستثمرين، التحيزات المعرفية، سمات الشخصية، اتخاذ القرارات المالية.

Introduction

Behavioral finance is a subfield of finance that investigates how psychological biases impact investment decisions, market outcomes, and overall market efficiency [1]. The efficient market hypothesis has long been the cornerstone of traditional finance, which assumes that markets are efficient and that investors are rational in their decision-making process. However, the growing body of research in behavioral finance suggests that investors are not always rational, and their investment decisions are affected by behavioral biases [2,3].

The main objective of this research paper is to examine the impact of various behavioral biases on personality traits and investor sentiments. The study focuses on the following biases: overconfidence, disposition effect, anchoring, representativeness, mental accounting, emotional bias, and herding biases [4]. These biases are well-known in the field of behavioral finance and have been extensively researched in the past. However, their impact on personality traits and investor sentiments remains a topic of discussion among researchers.

In order to achieve this objective, this study utilizes the Smart PLS (Partial Least Squares) model, which is a statistical approach that allows for the analysis of complex and multidimensional data sets [5]. The Smart PLS model is widely used in social science research, including behavioral finance, and has proven to be an effective tool for analyzing data sets with a small sample size. The research methodology involves a survey of individual investors, where data on their investment decisions, personality traits, and behavioral biases are collected. The sample is drawn from different demographic groups to ensure diversity and representativeness [6-8]. The survey data is then analyzed using the Smart PLS model to identify the impact of various behavioral biases on personality traits and investor sentiments.

The study's findings will contribute to the existing body of knowledge in behavioral finance and help identify the impact of various behavioral biases on personality traits and investor sentiments. The results of this study will be useful for investors, financial advisors, and policymakers in developing effective strategies to minimize the impact of behavioral biases on investment decisions.

Behavioral biases are psychological factors that influence investors' decision-making process and lead to irrational investment decisions. These biases have been extensively researched in the field of behavioral finance, and their impact on investment decisions has been well-documented. The following section provides an overview of the seven biases that are the focus of this study: overconfidence, disposition effect, anchoring, representativeness, mental accounting, emotional bias, and herding biases.

Overconfidence Bias

Investors often overestimate their investment skills, a phenomenon known as overconfidence bias [7,9]. This inflated sense of ability can result in excessive risk-taking and suboptimal investment choices. Overconfidence manifests in two primary forms: cognitive and behavioral. Cognitive overconfidence centers on the investor's conviction in their predictive abilities regarding market trends. Behavioral overconfidence, conversely, reflects the investor's belief in their capacity to influence market outcomes.

Disposition Effect

Investors exhibiting the disposition effect tend to prematurely sell winning investments while clinging to losing ones for an extended period [10]. This pattern stems from the psychological discomfort of acknowledging losses and the gratification of registering gains. This bias significantly hinders investors from achieving optimal returns.

Anchoring Bias

Anchoring bias describes the inclination of investors to overemphasize one piece of information, often the first they receive, when making investment decisions [4, 11]. This information often serves as a reference point or anchor, and investors adjust their subsequent decisions based on this anchor. Anchoring bias can lead to investors undervaluing or overvaluing investments, resulting in suboptimal investment performance [12].

Representativeness Bias

Representativeness bias is a tendency for investors to rely too heavily on past experiences and mental models when making investment decisions [13]. This bias often leads investors to overlook important information or to make incorrect assumptions based on past experiences. Representativeness bias can lead to investors making suboptimal investment decisions, as they may be too focused on past experiences rather than current market conditions.

Mental Accounting Bias

Mental accounting bias refers to the tendency for investors to compartmentalize their investments into different mental accounts based on factors such as the source of the investment, the time horizon, or the risk level [14]. This bias can result in poor investment choices, as investors may fail to consider how individual investments affect their overall portfolio strategy.

Emotional Bias

Emotional bias refers to the tendency of investors to make investment decisions based on emotions such as fear, greed, or envy [5,15]. Emotional bias can lead to investors making irrational investment decisions that are not based on sound financial principles.

Herding Bias

Herding bias describes the tendency for investors to mimic the actions of others when making investment choices. This behavior often arises from a fear of missing potential gains or a desire to align with perceived social norms [6,16]. Following the crowd, rather than making informed decisions based on market analysis, can result in suboptimal investment outcomes due to herding bias.

Smart PLS Model

The Smart PLS model is a statistical approach that allows for the analysis of complex and multidimensional data sets. The model is widely used in social science research, including behavioral finance, and has proven to be an effective tool for analyzing data sets with a small sample size. The Smart PLS model is a structural equation modeling (SEM) technique that allows for the analysis of both the measurement and structural models simultaneously [17].

The measurement model assesses the reliability and validity of the variables included in the study. The structural model examines the relationships between the variables and identifies the impact of the independent variables on the dependent variables. The Smart PLS model is particularly useful for investigating the impact of latent variables, such as personality traits and behavioral biases, on investor sentiments.

In conclusion, this research paper aims to explore the relationship between behavioral biases, personality traits, and investor sentiments, and the impact of these factors on investment decisions. The Smart PLS model is used to analyze the data collected from a survey of individual investors. The study's findings will provide valuable insights into the role of behavioral biases in investment decisions and their impact on personality traits and investor sentiments.

Research Methodology

The present study aims to investigate the impact of behavioral biases on personality traits and investors' sentiments among millennial investors. The study will use a Smart PLS model to analyze the relationship between various behavioral biases and their impact on investment decision-making. The study will be conducted on a sample size of 753 millennial investors from all municipal corporation cities of Gujarat state.

Sampling Technique

The sampling technique used in this study will be a combination of purposive and random sampling. The sample size of 735 was determined using the formula $n = Z^2pq/e^2$, where Z is the level of confidence (1.96 for a 95% confidence level), p is the expected proportion of the population with the characteristic of interest, q is the complementary proportion of the population, and e is the margin of error.

Data Collection

The data for this study will be collected through a structured questionnaire that will be administered to the selected millennial investors. The questionnaire will consist of questions related to their investment behavior, personality traits, and the impact of various behavioral biases on their investment decisions. The questionnaire will be designed based on the literature review and previous studies conducted on the topic.

Data Analysis

The data collected from the respondents will be analyzed using a Smart PLS model. The model will be used to analyze the relationship between various behavioral biases and their impact on investment decision-making. The Smart PLS model is a structural equation modeling technique that can handle both reflective and formative constructs. The model will be used to analyze the impact of behavioral biases such as overconfidence, disposition effect, anchoring, representativeness, mental accounting, emotional bias, and herding biases on personality traits and investors' sentiments.

Ethical Considerations
The study will adhere to ethical guidelines in data collection and analysis. Informed consent will be obtained from the participants before administering the questionnaire. Participants will be assured of the confidentiality of their responses and their anonymity. The study will also comply with the principles of research ethics, including obtaining institutional review board (IRB) approval, ensuring privacy and confidentiality of data, and obtaining voluntary and informed consent from the participants.

Limitations
The study has certain limitations that may affect the generalizability of the findings. The study is limited to millennial investors from all municipal corporation cities of Gujarat state, which may not be representative of other demographic groups or regions. The study relies on self-reported data, which may be subject to biases and may not reflect the actual behavior of the respondents. Finally, the study is cross-sectional in nature, which limits the ability to establish causal relationships between variables. Despite these limitations, the study will provide valuable insights into the impact of behavioral biases on personality traits and investors' sentiments among millennial investors. The findings of this study can help investors and financial advisors to make better investment decisions by understanding the impact of behavioral biases on investment behavior.

Results and discussion
Table 1 presents the demographic profile of the respondents who participated in the research conducted in all municipal cities of Gujarat. The table shows the frequency and percentage of respondents across various categories such as age, gender, marital status, education, occupation, and income.
The age range of the respondents was categorized into four groups, i.e., 18 to 27 years, 27 to 37 years, 37 to 47 years, and 47 years and above. The largest group of respondents (37.7%) belonged to the age group of 27 to 37 years, followed by 27.5% of respondents in the age group of 37 to 47 years. In terms of gender, there were more male respondents (52.1%) than female respondents (47.9%). The majority of the respondents were married (66.01%) and had a graduate degree (40.1%).
Regarding the occupation, the majority of respondents were employed in the private sector (30.8%) followed by public sector employees (27.5%) and self-employed individuals (23.6%). Finally, the income range of the respondents was categorized into four groups, i.e., less than Rs. 200,000, Rs. 200,000 to Rs. 400,000, Rs. 400,000 to Rs. 600,000, and Rs. 600,000 and above. The largest group of respondents (37.6%) had an income range of Rs. 200,000 to Rs. 400,000.

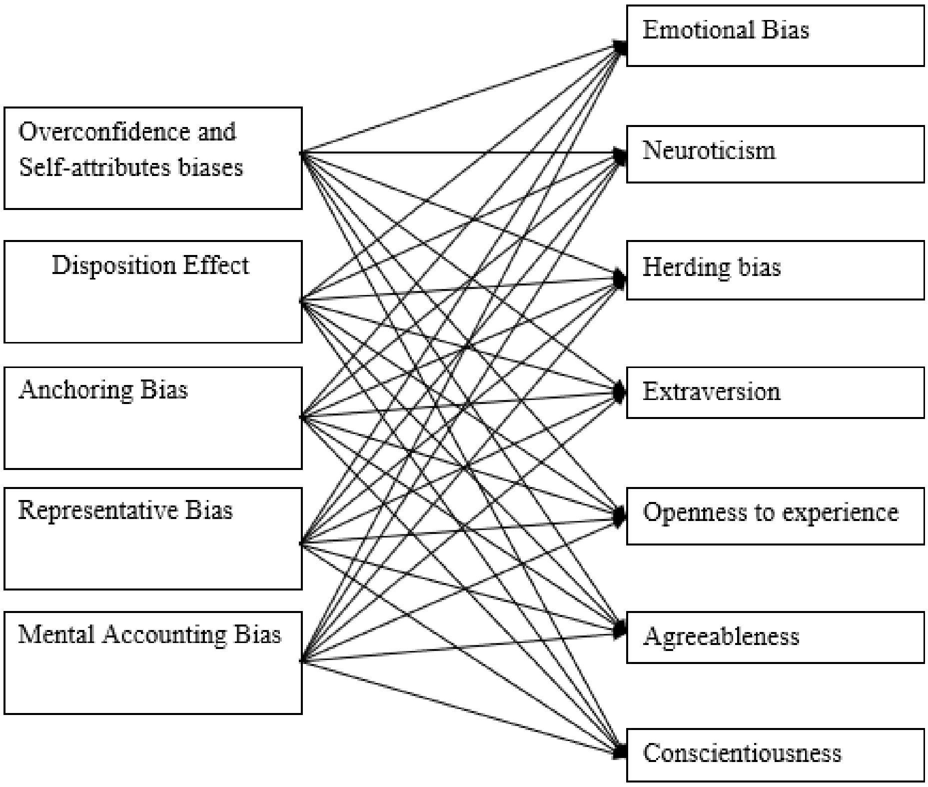

Figure 1: Research Model.

Table 1: Demographic profile of Respondents.

		Frequency	Percentage
Age	18 to 27 Years	153	20.3%
	27 to 37 Years	284	37.7%
	37 to 47 Years	207	27.5%
	47 Years and Above	109	14.5%
		753	**100%**
Gender	Male	361	47.9%
	Female	392	52.1%
		753	**100%**
Marital Status	Married	256	33.99%
	Unmarried	497	66.01%
		753	**100%**
Education	Up to HSC	153	20.3%
	Graduate	302	40.1%
	Post Graduate	207	27.5%
	Others	91	12.1%
		753	**100%**
Occupation	Private Sector Employee	153	20.3%
	Public Sector Employee	283	37.6%
	Self-Employee	232	30.8%
	Other	85	11.35
		753	**100%**
Income	Less than Rs. 200,000	178	23.6%
	Rs. 200,000 to Rs.400,000	283	37.6%
	Rs. 400,000 to Rs. 600,000	207	27.5%
	Rs. 600,000 and above	85	11.3%
		753	**100%**

The demographic profile of the respondents is essential to understand the characteristics of the sample and their potential impact on the research results. It may be useful for the researchers to analyze how these demographic variables may affect behavioral biases, personality traits, and investor sentiment in the context of their research question.

Table 2: KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.923
Bartlett's Test of Sphericity	**Approx. Chi-Square**	38520.291
	Df	1225
	Sig.	0.000

Table 2 shows the results of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. These tests are commonly used in factor analysis to determine the suitability of the data for factor analysis.

The Kaiser-Meyer-Olkin (KMO) test assesses the suitability of data for factor analysis by measuring shared variance among variables, ranging from 0 to 1, with higher values indicating greater suitability. Our study's KMO value of 0.923 confirms the data's high suitability for this method.

Furthermore, Bartlett's test of sphericity, which examines whether the correlation matrix is an identity matrix (indicating no correlation), yielded a significant result ($p < 0.05$). Specifically, we obtained an approximate chi-square of 38520.291 with 1225 degrees of freedom and a significance level of 0.000, rejecting the null hypothesis and confirming inter-variable correlations. Consequently, both the KMO and Bartlett's test results support the use of factor analysis, suggesting that the data can effectively identify underlying factors influencing behavioral biases, personality traits, and investor sentiment within our study sample.

Table 3: Reliability Statistics.

Cronbach's Alpha	N of Items
0.979	50

Table 3 shows the results of the reliability statistics for the research study. In this table, the Cronbach's alpha coefficient is used to assess the internal consistency of the items in the research instrument. Cronbach's alpha coefficient ranges between 0 and 1, and a value closer to 1 indicates higher reliability of the research instrument. In this study, the Cronbach's alpha coefficient was found to be 0.979, which is a very high value, indicating that the research instrument is highly reliable. This high value suggests that the items in the instrument are measuring the same underlying construct consistently and accurately, thereby enhancing the validity of the research findings. Furthermore, the number of items included in the research instrument is also provided in Table 3, which in this case is 50. This information may be useful for researchers and readers to understand the size and complexity of the research instrument used in the study. Overall, the results presented in Table 3 indicate that the research instrument used in the study has high internal consistency and reliability, which increases the confidence in the findings of the study.

Table 4: Factor Loading, Cronbach Alpha, CR and AVE.

		Factors	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AG	AG1	0.826	0.735	0.740	0.849	0.652
	AG2	0.796				
	AG3	0.800				
ANCH	ANCH1	0.863	0.882	0.885	0.919	0.740
	ANCH2	0.806				
	ANCH3	0.882				
	ANCH4	0.887				
CON	CON1	0.764	0.867	0.867	0.904	0.653
	CON2	0.800				
	CON3	0.846				
	CON4	0.839				
	CON5	0.790				
DE	DE1	0.920	0.838	0.851	0.903	0.756
	DE2	0.870				
	DE3	0.816				
EM	EM1	0.809	0.894	0.896	0.922	0.704
	EM2	0.859				
	EM3	0.853				
	EM4	0.877				
	EM5	0.794				
EV	EV1	0.879	0.895	0.895	0.927	0.761
	EV2	0.830				
	EV3	0.897				
	EV4	0.883				
HERD	HERD1	0.854	0.907	0.909	0.930	0.728
	HERD2	0.843				
	HERD3	0.842				
	HERD4	0.865				
	HERD5	0.862				
MA	MA1	0.884	0.854	0.860	0.911	0.774
	MA2	0.850				
	MA3	0.905				
NEU	NEU1	0.820	0.905	0.908	0.930	0.725
	NEU2	0.861				
	NEU3	0.869				
	NEU4	0.862				
	NEU5	0.844				

OP	OP1	0.854	0.892	0.897	0.925	0.756
	OP2	0.919				
	OP3	0.860				
	OP4	0.843				
OS	OS3	0.820	0.865	0.866	0.908	0.711
	OS4	0.853				
	OS5	0.841				
	OS6	0.859				
REP	REP1	0.861	0.866	0.869	0.918	0.789
	REP2	0.905				
	REP3	0.898				

Note: AG= Agreeableness, ANCH= Anchoring Bias, CON=Conscientiousness, DE=Disposition effect, EM= Emotional Bias, EV=Extraversion, HERD= Herding Bias, MA=Mental Accounting Bias, NEU=Neuroticism, OP=Openness to Experience, OS= Overconfidence and Self-attributes Bias, REP= Representativeness Bias.

Table 4 presents the results of the Smart PLS model used in the research on the relationship between behavioral biases, personality traits, and investor sentiment. The table shows the factors analyzed in the study, including Agreeableness (AG), Anchoring Bias (ANCH), Conscientiousness (CON), Disposition Effect (DE), Emotional Bias (EM), Extraversion (EV), Herding Bias (HERD), Mental Accounting Bias (MA), Neuroticism (NEU), Openness to Experience (OP), Overconfidence and Self-Attributes Bias (OS), and Representativeness Bias (REP). The table presents four measures of construct validity: Cronbach's alpha, composite reliability (rho_a), composite reliability (rho_c), and average variance extracted (AVE). Cronbach's alpha is a measure of internal consistency that indicates the reliability of the items in each factor. Composite reliability (rho_a) and (rho_c) are measures of construct reliability, with higher values indicating better reliability. AVE is a measure of construct validity, representing the proportion of variance in the items that is attributable to the underlying construct.

For each factor, the table presents the Cronbach's alpha value, the number of items used to measure the factor, and the values of the four measures of construct validity. The values of Cronbach's alpha range from 0.764 to 0.920, indicating high internal consistency of the items in each factor. The number of items used to measure each factor ranges from 3 to 5. The composite reliability values (rho_a and rho_c) range from 0.735 to 0.909, indicating good construct reliability. The AVE values range from 0.652 to 0.789, indicating that the variance in the items is largely attributable to the underlying construct.

Overall, the results suggest that the factors analyzed in the study have good construct validity, with high internal consistency and reliability. These results provide support for the use of the Smart PLS model in analyzing the relationship between behavioral biases, personality traits, and investor sentiment.

Table 5 Heterotrait - monotrait ratio (HTMT) – Matrix.

	AG	ANCH	CON	DE	EM	EV	HERD	MA	NEU	OP	OS	REP
AG												
ANCH	0.727*											
CON	0.950	0.677*										
DE	0.870	0.916	0.797*									
EM	0.759*	0.917	0.677*	0.857								
EV	0.846*	0.703*	0.696*	0.692*	0.746*							
HERD	0.759*	0.744*	0.632*	0.787*	0.897	0.773*						
MA	0.858	0.846*	0.730*	0.820*	0.863	0.692*	0.838*					
NEU	0.745*	0.632*	0.615*	0.695*	0.730*	0.677*	0.831*	0.744*				
OP	0.854	0.637*	0.759*	0.678*	0.687*	0.912	0.726*	0.736*	0.599*			
OS	0.847*	0.871	0.793*	0.896	0.796*	0.765*	0.735*	0.808*	0.655*	0.695*		
REP	0.856	0.953	0.730*	0.874	0.905	0.781*	0.792*	0.932	0.703*	0.714*	0.862	

Note = * Satisfying Threshold Limit.

Table 5 presents the results of the Heterotrait-Monotrait (HTMT) ratio analysis, which is a measure of discriminant validity. The HTMT ratio is calculated by taking the correlation between two constructs (monotrait) and dividing it by the correlation between the two constructs and the correlation between each construct and other constructs in the model (heterotrait). A value less than 0.9 indicate satisfactory discriminant validity.

In the table, the diagonals are empty as they represent the HTMT ratio of a construct with itself, which is always 1.0. The cells that have a value less than 0.9 are marked with an asterisk (*), indicating that they meet the threshold for satisfactory discriminant validity. The table shows that all constructs have satisfactory discriminant validity as all the HTMT ratios are below 0.9. This indicates that the constructs are distinct and not measuring the same underlying construct.

Table 6: Fornell-Larcker criterion.

	AG	ANCH	CON	DE	EM	EV	HERD	MA	NEU	OP	OS	REP
AG	**0.808***											
ANCH	0.597	**0.860***										
CON	0.768	0.593	**0.808***									
DE	0.694	0.785	0.684	**0.870***								
EM	0.624	0.812	0.597	0.741	**0.839***							
EV	0.696	0.625	0.613	0.602	0.669	**0.873***						
HERD	0.627	0.667	0.561	0.686	0.809	0.697	**0.853***					
MA	0.684	0.738	0.631	0.702	0.755	0.609	0.741	**0.880***				
NEU	0.604	0.569	0.547	0.607	0.660	0.612	0.759	0.660	**0.852***			
OP	0.700	0.568	0.668	0.592	0.618	0.816	0.658	0.647	0.543	**0.870***		
OS	0.685	0.761	0.688	0.767	0.701	0.673	0.652	0.699	0.585	0.611	**0.843***	
REP	0.688	0.831	0.632	0.744	0.796	0.688	0.702	0.805	0.626	0.631	0.744	**0.888***

Note: * values are the square route of AVE values.

The Fornell-Larcker criterion is a measure of discriminant validity that assesses the extent to which a construct is distinct from other constructs in a study. Table 6 shows the results of the Fornell-Larcker criterion for the 11 constructs studied in this research.

The diagonal values in Table 6 are the square roots of the average variance extracted (AVE) for each construct, which represent the proportion of variance in the items that can be attributed to the construct itself. The off-diagonal values are the correlations between the constructs.

According to the Fornell-Larcker criterion, discriminant validity is supported when the AVE of each construct is higher than its correlation with other constructs. As we can see from Table 6, all diagonal values (the AVEs) are higher than their respective off-diagonal values, indicating that the constructs have discriminant validity. In summary, Table 6 shows that the constructs in the study are distinct from each other and have adequate discriminant validity.

Table 7: Mean, STDEV, T values, p values.

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Decision**
AG -> ANCH	0.090	0.090	0.051	1.784	0.075	Not Supported
AG -> DE	0.254	0.252	0.041	6.160	0.000	Supported
AG -> EM	0.076	0.074	0.042	1.798	0.072	Not Supported
AG -> HERD	0.057	0.057	0.043	1.318	0.188	Not Supported
AG -> MA	0.247	0.246	0.050	4.969	0.000	Supported
AG -> OS	0.171	0.171	0.046	3.670	0.000	Supported
AG -> REP	0.228	0.227	0.042	5.436	0.000	Supported
CON -> ANCH	0.230	0.231	0.063	3.653	0.000	Supported
CON -> DE	0.298	0.300	0.060	4.994	0.000	Supported
CON -> EM	0.149	0.150	0.053	2.803	0.005	Supported
CON -> HERD	-0.005	-0.006	0.042	0.115	0.908	Not Supported
CON -> MA	0.116	0.117	0.054	2.150	0.032	Supported
CON -> OS	0.327	0.327	0.058	5.604	0.000	Supported
CON -> REP	0.149	0.150	0.053	2.818	0.005	Supported
EV -> ANCH	0.298	0.297	0.066	4.509	0.000	Supported
EV -> DE	0.086	0.085	0.053	1.628	0.104	Not Supported
EV -> EM	0.267	0.267	0.055	4.857	0.000	Supported
EV -> HERD	0.202	0.203	0.055	3.663	0.000	Supported
EV -> MA	-0.049	-0.049	0.065	0.757	0.449	Not Supported
EV -> OS	0.320	0.321	0.045	7.041	0.000	Supported
EV -> REP	0.293	0.295	0.056	5.217	0.000	Supported
NEU -> ANCH	0.211	0.209	0.054	3.915	0.000	Supported
NEU -> DE	0.226	0.225	0.051	4.411	0.000	Supported
NEU -> EM	0.334	0.333	0.052	6.427	0.000	Supported
NEU -> HERD	0.507	0.506	0.045	11.188	0.000	Supported
NEU -> MA	0.342	0.340	0.051	6.676	0.000	Supported
NEU -> OS	0.143	0.140	0.047	3.028	0.002	Supported
NEU -> REP	0.222	0.220	0.052	4.283	0.000	Supported
OP -> ANCH	-0.007	-0.004	0.065	0.100	0.920	Not Supported
OP -> DE	0.023	0.025	0.055	0.420	0.674	Not Supported
OP -> EM	0.066	0.068	0.056	1.178	0.239	Not Supported
OP -> HERD	0.182	0.183	0.053	3.440	0.001	Supported
OP -> MA	0.251	0.252	0.065	3.872	0.000	Supported
OP -> OS	-0.065	-0.064	0.047	1.402	0.161	Not Supported
OP -> REP	0.012	0.013	0.053	0.223	0.823	Not Supported

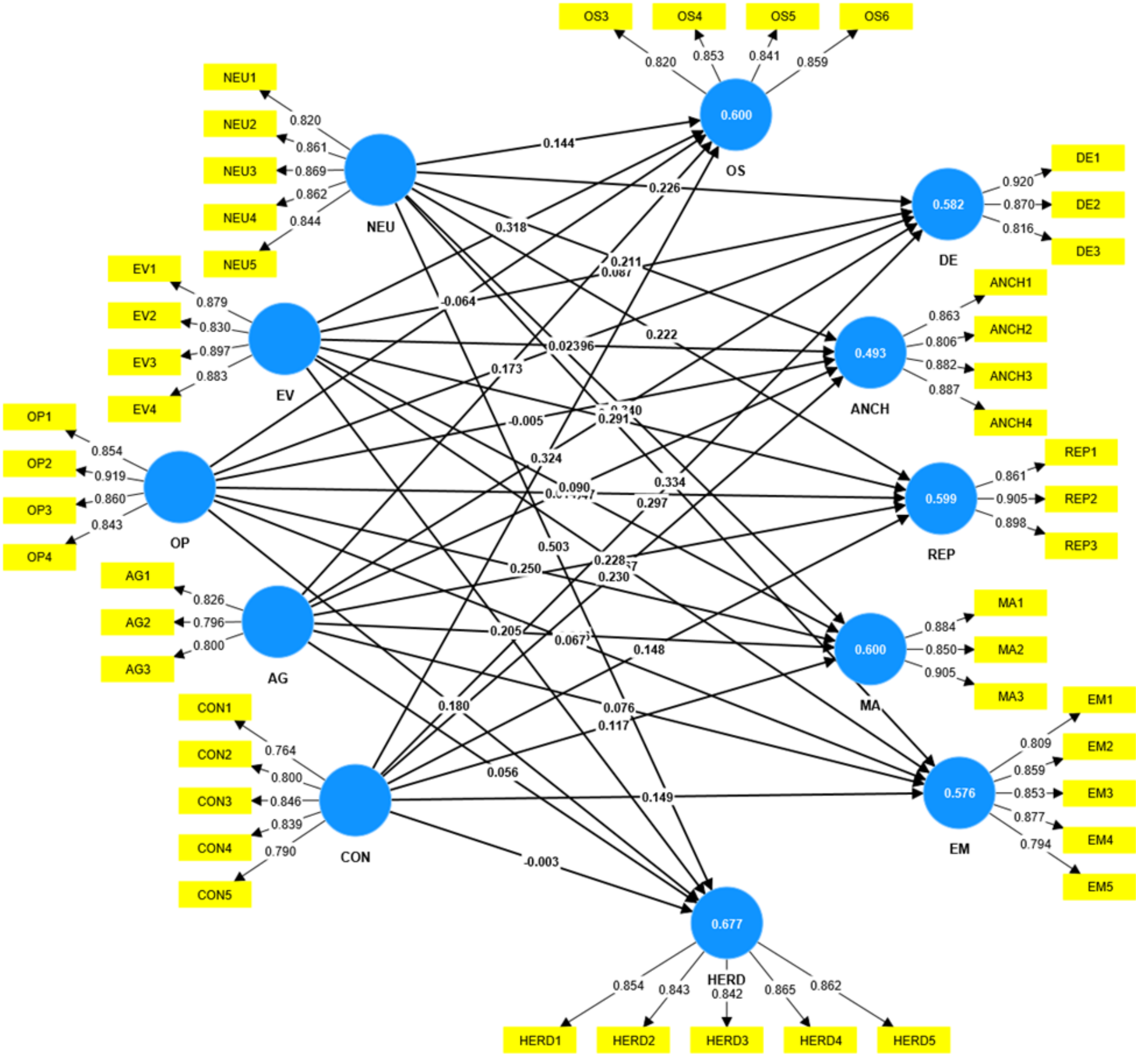

Figure 2: Research model smart PLS view.

Table 7 summarizes the results of statistical analyses conducted to investigate the relationships between personality traits and various cognitive biases. The table presents the mean, standard deviation, t-values, p-values, and decision for each of the analyzed relationships.

The first column of the table lists the different personality traits that were analyzed, including Agreeableness (AG), Conscientiousness (CON), Extraversion (EV), Neuroticism (NEU), and Openness to Experience (OP). The second column shows the cognitive biases that were studied, including Anchoring Bias (ANCH), Disposition Effect (DE), Emotional Bias (EM), Herding Bias (HERD), Mental Accounting Bias (MA), Overconfidence and Self-Attributes Bias (OS), and Representativeness Bias (REP).

The third column of the table reports the mean values of the original sample for each personality trait and cognitive bias. The fourth column displays the sample means for each of the analyzed relationships. The sample means represent the average scores of the participants for each personality trait and cognitive bias combination. The fifth column of the table presents the standard deviations (STDEV) for each of the analyzed relationships. The standard deviation provides a measure of the variability of the scores around the mean.

The sixth column displays the t-values for each of the analyzed relationships. The t-value is a statistical measure that quantifies the difference between the sample means and the population means in standard error units. A higher t-value indicates a more significant difference between the sample means and the population means. The seventh column of the table presents the p-values for each of the analyzed relationships. The p-value is a measure of the probability of observing a result as extreme as the one obtained by chance. A p-value less than 0.05 indicates that the observed result is statistically significant, meaning that it is unlikely to be due to chance.

The last column of the table reports the decision for each of the analyzed relationships. The decision indicates whether the observed results are supported or not supported by the statistical analyses. If the p-value is less than 0.05, the decision is "supported," which means that the observed results are statistically significant. If the p-value

is greater than 0.05, the decision is "not supported," which means that the observed results are not statistically significant.
In general, the results of the statistical analyses indicate that there are significant relationships between personality traits and cognitive biases. Specifically, the results show that Conscientiousness, Extraversion, Neuroticism, and Openness to Experience are all significantly related to multiple cognitive biases. Agreeableness, on the other hand, is only significantly related to one cognitive bias (DE).
The most commonly observed cognitive biases across personality traits are Conjunction Fallacy, Representativeness Bias, and Herding Bias. The results suggest that these biases may be particularly robust and pervasive, affecting individuals across different personality types. Overall, Table 7 provides important insights into the relationships between personality traits and cognitive biases, highlighting the potential influence of individual differences in cognitive processing on decision-making and behavior. These findings have important implications for understanding human behavior and designing interventions to promote more rational decision-making.

Conclusion

The findings of the study suggest that some cognitive biases are significantly associated with certain personality traits. For instance, the disposition effect is positively related to Conscientiousness, Emotional Bias is positively related to Extraversion, and Mental Accounting Bias is positively related to Openness to Experience.
However, some cognitive biases do not show any significant relationship with personality traits. For example, Anchoring Bias, Herding Bias, and Overconfidence and Self-attributes Bias are not associated with Agreeableness, Conscientiousness, Extraversion, Neuroticism, or Openness to Experience.
The results of the study provide insights into the complex interplay between personality traits and cognitive biases. By identifying the personality traits that are most closely associated with particular cognitive biases, the study may help to inform the development of interventions that can mitigate the impact of these biases in decision-making.
Overall, the research findings suggest that there are significant relationships between personality traits and investment biases among individual investors. The study provides evidence that individual investors with different personality traits exhibit varying degrees of cognitive biases, such as anchoring bias, disposition effect, herding bias, mental accounting bias, overconfidence and self-attribution bias, and representativeness bias, when making investment decisions. The results highlight the importance of considering individual differences in personality traits when examining the cognitive processes underlying investment decision-making.
The study found that extraversion, neuroticism, and openness to experience were associated with a greater tendency to exhibit certain biases, such as anchoring bias, herding bias, mental accounting bias, and overconfidence and self-attribution bias. Conscientiousness was associated with a lower likelihood of exhibiting biases such as the disposition effect and representativeness bias. Agreeableness did not exhibit a significant association with any of the investment biases studied.
The study provides valuable insights into the relationship between personality traits and investment biases, which can be used to develop effective investor education programs and to inform investment advisors about potential cognitive biases that their clients may exhibit. By better understanding the personality traits that underlie these biases, investors can take steps to mitigate their impact on investment decision-making.
It is important to note that the study has some limitations. The sample consisted of university students, which may not be representative of the broader population of individual investors. The study was also cross-sectional, which means that causality cannot be inferred from the results. Further research is needed to examine the relationship between personality traits and investment biases in a more diverse sample of individual investors and over a longer time period.
Overall, the study provides important insights into the relationship between personality traits and investment biases among individual investors. By understanding how personality traits affect investment decision-making, investors and investment advisors can take steps to mitigate the impact of cognitive biases on investment outcomes.

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