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Behavioral Biases and Regional Diversity: An In-Depth Analysis of Their Influence on Investment Decisions - A SEM and MICOM Approach

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Abstract: The Basic purpose of the study was to understand the impact of behavioral biases on Global Investors investment Decisions and whether there is any significant difference of the impact on investment Decisions of Global investors due to regional diversity. The data was collected from 467 Global investors from China and India SEM was used to test the hypothesis and Followed by Multi- group analysis. The results revealed that Behavioral biases have a significant on investment decisions of Global Investors. The impact was found more on India Global investors than that of China. The insight into how regional diversity can magnify or attenuate these biases offers valuable guidance for global investment firms seeking to tailor their services to a culturally diverse clientele. Understanding the interplay between behavioral biases and regional disparities allows for the development of region-specific financial products and advice, better aligning investment strategies with the unique needs and risk tolerance of investors from different parts of the world. The originality of this research lies in its nuanced examination of how behavioral biases, in conjunction with regional disparities, can offer valuable insights for both investors and financial practitioners, enhancing our comprehension of the intricate dynamics at play in the global investment sphere.
Keywords: Herding Bias, Mental Accounting, Loss Aversion, Confirmation Bias, Status Quo and Investment Decisions.

I. INTRODUCTION

Investment decisions require careful consideration and research to ensure that the investment will yield a positive return. Traditional Financial belief was based on the postulation that most Investors behave rationally whenever it comes to ambiguity and uncertainty in making investment decisions, backed by theories like the Efficient market hypothesis, However, the same paradigm was questioned and argued by [1] and a new belief emerged that became popular with the name of behavioral finance, that believes investors' rationality is been influenced by several factors like personality cognitive and emotional biases [2] Studies divulge that investment decisions are dominated by several factors like demographic factors (i.e., income, gender, age and education) Markets (i.e., transaction cost, expected return, market environment, the actual rate of return etc.), investor's personal characteristics (i.e. Personality, emotions, values & risk appetite) and many other related factors like financial risk perception and risk tolerance influence investors' investment decisions . Studies revealed investors' financial decisions are influenced by psychological behavioral factors. Previous studies had revealed theoretically and empirically that the personal features of an investor have a serious impact on investing and portfolio framing. Since the 1990s many Theoretical and empirical studies were carried out, that deviated from the existing literature and opened the gates and promoted the research in the field of behavioral finance. Economists in the field of behavioral finance proved through various studies how investors behave irrationally in the financial markets. They used information from the many anthropological, psychological, and sociological cognitive-behavioral theories on human behavior. They developed two key ideas in the field of behavioral finance, known as Heuristics and Prospect theory, respectively. Because of psychological biases, [3] discovered evidence of irrationality in the Indian equities market. The financial markets are influenced by uncertainty that can nudge the investors towards investment decisions propelling them to employ heuristics. Several studies have recently compiled the research on behavioral biases. However, the available literature provides a valuable insights about the financial behavior, but there is a need of a comprehensive review that can cover all the behavioral biases [4-6]. Understanding behavioral biases in investment decisions is crucial because humans are not rational decision-makers, and our emotions and cognitive biases can lead us to make poor investment decisions [7]. Behavioral biases can cloud our judgment and cause us to deviate from our long-term investment goals. By understanding these behavioral biases, investors can become more aware of their own tendencies and develop strategies to counteract them, leading to better investment decisions and ultimately better financial outcomes [8, 9]. The present manuscript is an attempt to compile and understand the insights of the area to fill the gap in the literature. This paper aims to provide an extensive examination of the critical interplay between behavioral biases and regional diversity in the context of investment decisions. By delving into the various cognitive and emotional biases that often influence investors, such as overconfidence, loss aversion, and herd mentality, and juxtaposing these with the distinctive economic, cultural, and regulatory characteristics of different regions, this research seeks to elucidate how these factors jointly impact investment choices [10]. Understanding the complex relationship between behavioral biases and regional diversity is of paramount importance for both individual and institutional investors as it can shed light on the rationality and efficiency of financial markets, potentially leading to improved decision-making strategies and risk management in the realm of investments [11]. This paper holds significant importance in the field of finance and investment for several reasons. First, it addresses a critical gap in the literature by combining two vital elements, behavioral biases, and regional diversity, to offer a comprehensive understanding of investment decision-making. Such an analysis can contribute to the development of more accurate predictive models and investment strategies [12]. Second, recognizing the impact of behavioral biases within the context of regional diversity allows for a more nuanced comprehension of market dynamics. Investors and financial professionals can use this insight to make more informed, culturally-sensitive, and region-specific decisions [13]. Third, in an increasingly globalized world, understanding the interplay of these factors can enhance risk management and improve portfolio diversification strategies. Overall, this paper has the potential to advance the knowledge and practices in investment, benefiting investors, financial institutions, and the broader financial markets [14]. This paper aims to explore the impact of behavioral biases and regional diversity on investment decisions. By employing Structural Equation Modeling (SEM) and the Modified Input-Output Model (MICOM), it seeks to provide a comprehensive analysis of how these factors interact in shaping investment outcomes. The purpose is to offer insights into the complexities of investment decision-making processes influenced by psychological biases and regional variations, aiding investors in navigating diverse markets more effectively. Through a rigorous examination, this study intends to contribute to a deeper understanding of the intricate dynamics guiding investment behavior in global markets.

II. LITERATE REVIEW

1. INVESTMENT DECISIONS

Investment decisions are influenced by a multitude of factors, including regional diversity, which plays a pivotal role in shaping investment strategies and outcomes. Researchers have extensively explored how geographical variations impact investment choices and performance. [15] Emphasized the importance of considering regional differences, asserting that the varying economic and institutional conditions across regions can significantly affect investment returns. Additionally, [16]argued that the regulatory environment in a specific region can impact investment decisions, as it directly affects the ease of doing business. This regulatory perspective was further substantiated by [17]who examined the relationship between legal institutions and investment strategies, showing that regional legal systems exert a substantial influence on foreign direct investment decisions. Moreover, cultural diversity within regions has been recognized as a critical factor influencing investment choices. [18] Highlighted the role of culture in shaping the investment decisions of individuals and institutions. They found that cultural factors, such as risk tolerance and investment time horizons, vary significantly across regions, leading to diverse investment behaviors. Building on this,[19, 20] investigated the impact of cultural dimensions on asset allocation decisions, revealing that regional cultural values can be powerful predictors of investment choices. In recent years, the importance of environmental, social, and governance (ESG) factors has gained prominence in the context of investment decisions. Here, regional diversity becomes relevant as regulatory and cultural aspects shape the ESG landscape in each area. Research by [21] highlighted that corporate governance practices differ significantly by region, and these differences influence investment decisions and performance. Investment decisions are undeniably influenced by regional diversity, encompassing economic, institutional, regulatory, and cultural aspects. Researchers have underlined the necessity of understanding these regional nuances when making investment choices [22, 23] Recognizing these factors is essential for investors and financial professionals in developing effective strategies that consider the diverse nature of global markets, thus enhancing investment performance and risk management.

H: Regional Diversity has a significant impact on impact on investment decisions.

2. HERDING BIAS AND INVESTMENT DECISIONS

Herding bias, a behavioral tendency where individuals tend to follow the crowd rather than making independent investment decisions, has garnered significant attention in the field of finance due to its far-reaching implications [24]. This bias stems from the fear of missing out on potential gains or avoiding losses when others appear to be making similar choices. Extensive research has shed light on the prevalence of herding behavior in financial markets and its consequences. Early work by [25]provided insights into the existence of herding among institutional investors, demonstrating how they often imitate the actions of their peers. These findings were substantiated by [26]who illustrated that mutual fund managers tend to follow prevailing market trends rather than making unique investment choices. Furthermore, [27] investigated herding behavior in stock markets and found that this bias intensifies during periods of high uncertainty or market turbulence, suggesting that emotional reactions play a crucial role in herding [28].

H1: Herding Bias has a significant Impact on investment decisions.

3. STATUS QUO AND INVESTMENT DECISIONS

The status quo bias is a well-documented behavioral phenomenon that significantly affects investment decisions [29]. This cognitive bias reflects individuals' tendencies to maintain their current portfolio or investment positions rather than making changes, even when evidence suggests that changes may be beneficial. Numerous studies in finance and behavioral economics have explored the implications of the status quo bias in the context of investment decisions [30]. The status quo bias also extends to investment professionals. [31] found evidence of inertia among financial advisors who tend to recommend portfolios that resemble the current market conditions, even when market dynamics change. This behavior can lead to herding and create potential inefficiencies in investment recommendations. Mitigating the status quo bias in investment decisions has been a subject of considerable interest. [24] demonstrated that carefully designed nudges, such as changing the default investment option in retirement plans, can help individuals overcome their inertia and make more appropriate choices [32].

H2: Status Quo has a significant Impact on investment decisions.

4. CONFIRMATION BIAS AND INVESTMENT DECISIONS

Confirmation bias, a pervasive cognitive bias, has been identified as a critical factor influencing investment decisions [33]. This bias occurs when individuals favor information that confirms their pre-existing beliefs or hypotheses while dismissing or downplaying evidence that contradicts them. Extensive research in finance and behavioral economics has explored the implications of confirmation bias in the context of investment decisions. [34] examined the behavior of individual investors and found that they exhibit a strong tendency to seek out and process information that confirms their current investment positions. Investors often check their portfolios more frequently when they are performing well, reinforcing their beliefs, and avoiding information that might prompt them to reconsider their investments [35]. This behavior can lead to a reluctance to sell underperforming assets and an over commitment to successful ones, ultimately affecting portfolio diversification and returns. Researchers have also explored the consequences of confirmation bias on the performance of professional investors. [36] found that mutual fund managers display a preference for information that supports their investment decisions, potentially leading to herding behavior and inefficiencies in market pricing.

H3: Confirmation has a significant Impact on investment decisions.

5. LOSS-AVERSION BIAS AND INVESTMENT DECISIONS

Loss-aversion bias, a fundamental component of prospect theory developed by [37], plays a pivotal role in shaping investment decisions. It reflects individuals' strong inclination to weigh potential losses more heavily than

gains, leading to risk-averse behaviors and suboptimal investment choices. Extensive research within the fields of behavioral economics and finance has focused on understanding the implications of loss-aversion bias in investment decisions. The consequences of loss-aversion bias extend to professional investors as well. [38] Examined the behavior of institutional investors and found that they also exhibit a reluctance to sell losing investments. This behavior, driven by the aversion to realizing losses, can lead to market inefficiencies and distortions in asset pricing. Mitigating the influence of loss-aversion bias on investment decisions is crucial. [39] proposed the concept of "behavioral portfolio theory," which incorporates psychological factors like loss aversion into traditional portfolio theory [40]. This approach suggests that investors should allocate assets in a way that aligns with their risk preferences and psychological biases, thus helping to mitigate the adverse effects of loss aversion [41].
H4: Loss Aversion has a significant Impact on investment decisions.

6. MENTAL ACCOUNTING BIAS AND INVESTMENT DECISIONS

Mental accounting bias is a prominent cognitive bias that significantly shapes investment decisions by segmenting investments into distinct mental accounts based on perceived categories or labels, rather than considering them as part of an overall portfolio [42]. This cognitive bias, first introduced by [43], has been a focal point of research within the fields of behavioral economics and finance, revealing its implications for investor behavior. Barber and [44] delved into the behavior of individual investors and identified mental accounting bias as a key factor in their suboptimal decision-making. Investors tend to create separate mental accounts for different investments, leading to suboptimal asset allocation, overconfidence in the performance of individual investments, and reluctance to sell underperforming assets due to their original categorization. Mental accounting bias can also affect professional investors. Researchers such as [45]examined the behavior of mutual fund managers and found evidence of this bias in their investment choices. Fund managers may allocate resources to different mental accounts within their portfolios, leading to inefficiencies and suboptimal risk-return trade-offs [46].
H5: Mental Accounting has a significant Impact on investment decisions.

III. MATERIAL & METHODS

The research methodology for a study titled "Behavioral Biases and Regional Diversity: An In-Depth Analysis of Their Influence on Investment Decisions - A MICOM Approach" involves outlining the systematic approach and techniques used to collect, analyze, and interpret data to achieve the study's objectives. This study will employ a quantitative research design. We will gather numerical data and utilize statistical methods to analyze the relationships between behavioral biases, regional diversity, and investment decisions.

1. MEASURES

In the current study, all the 35 measurement items that were used in the study to find the relationship among selected variables, and all the items were taken from existing literature. All the necessary adjustment was made to find the relationship among the selected variables. The survey used a five-point Likert scale, with "1" denoting "strongly disagree" and "5" denoting "strongly agree." The sources of the measurement tools are shown in Table I.

2. DATA COLLECTION

The data was collected through a structured questionnaire of 35 points. These questionnaires were shared through emails and WhatsApp among Indian and Chinese Global investors, who invest in various financial markets. The sample Composed for this study was 467 respondents, out of which the highest number was from India i.e. 247 respondents 52.41 % followed by China with 220 (47.69%).

It was observed that almost 74.08 % of Global Investors invest in stock for higher return and capital growth, followed by Real Estate and precious metals, and only 29% of Global Investors had shown interest in government bonds and other debt instruments.

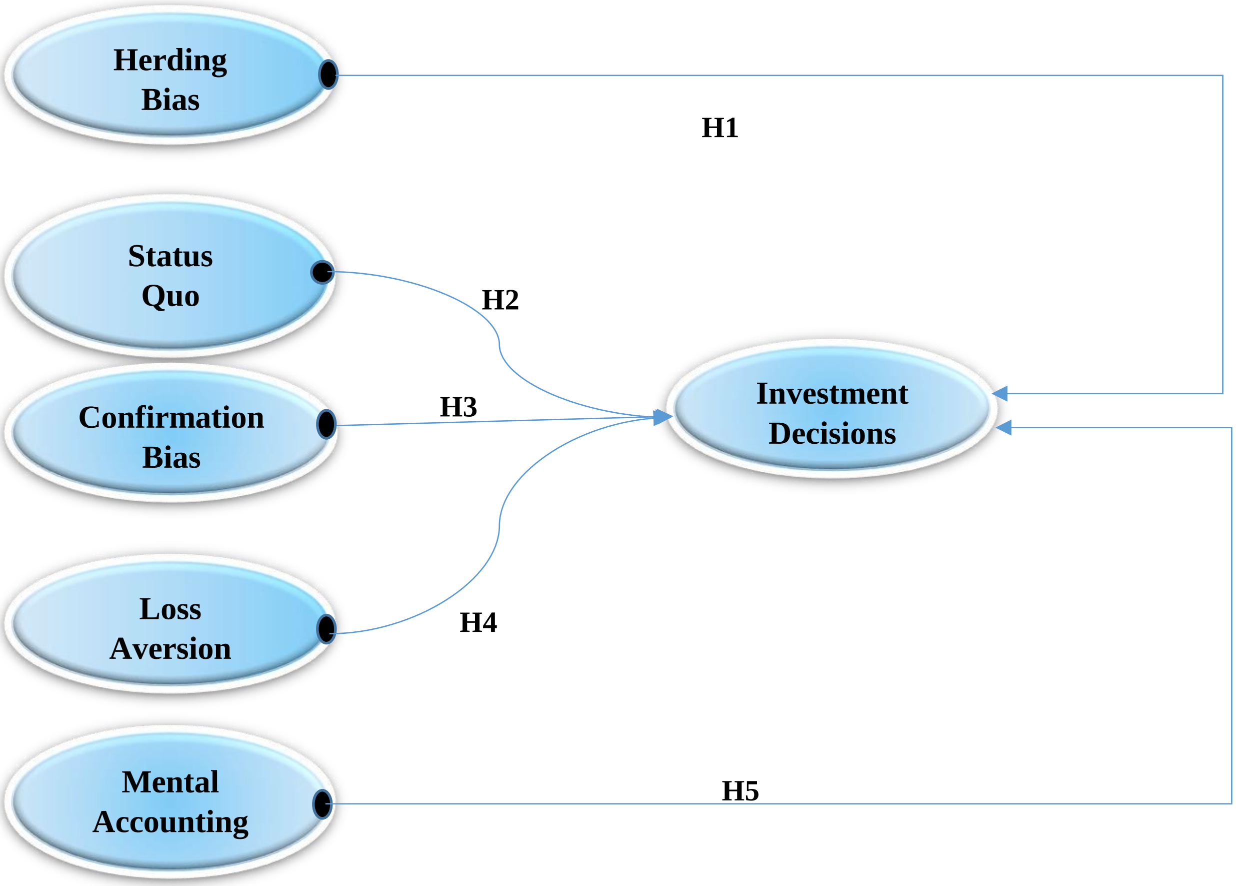

FIGURE 1. Theoretical framework authors' own elaboration.

The Conceptual Framework shown figure 1 shows the relationship between Behavioral Biases and investment decisions, the Model is based on five behavioral biases and investment Decisions. The Model was developed to test behavioral biases diversity among Chinese and Indian Investors.

3. HYPOTHESIS DEVELOPED

H: Regional Diversity has a significant impact on impact on investment decisions.

H1: Herding Bias has a significant Impact on investment decisions.

H2: Status Quo has a significant Impact on investment decisions.

H3: Confirmation has a significant Impact on investment decisions.

H4: Loss Aversion has a significant Impact on investment decisions.

H5: Mental Accounting has a significant Impact on investment decisions.

4. SOURCE OF MEASUREMENT AND ITEMS

Table 1. Source of measurement and items.

S/No	Factor	Items	Source
1	**Herding**	I follow social blogs/forums before purchasing/selling a security	Baker et al. (2019
		I follow others in all my investment decisions	Baker et al. (2019
		I prefer to invest in the assets that other investors are buying	Baker et al. (2019
2	**Mental Accounting**	I do not consider returns from income and capital appreciation separately.	Ahmad et al. (2017)
		I earmark the investments purpose wisely and maintain them separately	Baker et al. (2019)
		I categorize my investments into various purposes such as leisure, children's education and so on	Ritika & Kishor (2020)
3	**Status quo bias**	I like to sell or modify inherited investments.	Ritika & Kishor (2020)
		I keep holding the investments because they are familiar to me	Ritika & Kishor (2020)
		I think about changing my portfolio, but many times I do not change it	Ritika & Kishor (2020)
4	**Loss-aversion**	I do not avoid an investment when I fear the loss	Baker et al. (2019)
		I never sell an investment at a loss with an expectation that it will eventually improve	Chandra et al. (2017)
		I avoid taking decisions with the fear of incurring losses	Ritika & Kishor (2020)
5	**Confirmation Bias**	I am not selective in collecting information about the investments made by me.	Ritika & Kishor (2020)
		I value positive information more than negative information regarding my investment choices	Ritika & Kishor (2020)
		When an investment is not going well, I seek information that confirms I made the right decision	Ritika & Kishor (2020)
6	**Investment Decision**	Our investment in stocks has a high degree of safety	Qureshi (2012)
		Our investment has the ability to meet interest payments	Qureshi (2012)
		Our investment repays the principal at maturity	Qureshi (2012)
		Our investment has a lower risk compared to the market in general	Qureshi (2012)

IV.DATA ANALYSIS

After the data was collected, the filtration of the data was done in excel in which data was converted into respective codes, missing frequencies were filled accordingly. Normality of the data was tested through (1) Shapiro-Wilk test in SPSS and Cramer-Von test in Smart PLS 4. The results of both the tests show that all the constructs have a significant value of < 0.05, confirming the non-normality of the data.

1. MEASUREMENT MODEL ASSESSMENT

Once the non-normality was confirmed and the model was complex, Structural equation Modelling was found appropriate for hypothesis testing. Factor loading of each item was calculated and the Multicollinearity of each item followed by reliability and discriminant validity, after the assessment of the measurement model, hypothesis testing was done in structural model.

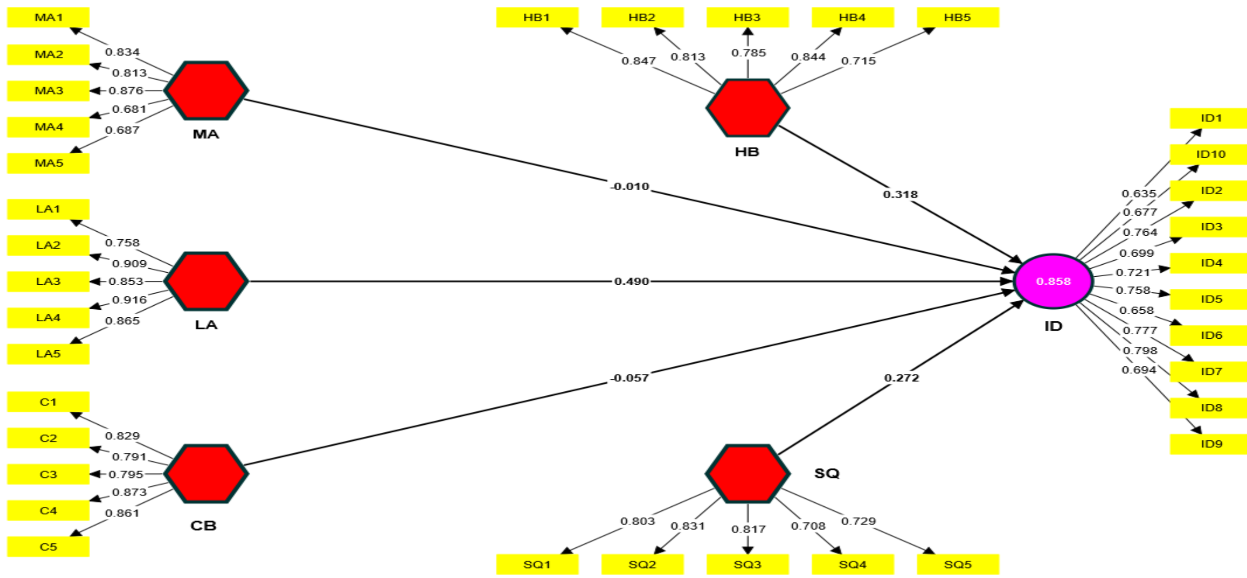

FIGURE 2. Measurement model

Source: Smart PLS 4

Figure 2 is the result of the measurement model in which factor loading of each item is shown in each construct Relationship.

Table 2. Factor Loading

Items	CB	HB	ID	LA	MA	SQ
C1	0.829					
C2	0.791					
C3	0.795					
C4	0.873					
C5	0.861					
HB1		0.847				
HB2		0.813				
HB3		0.785				
HB4		0.844				
HB5		0.715				
ID1			0.635			
ID10			0.677			
ID2			0.764			
ID3			0.699			
ID4			0.721			
ID5			0.758			
ID6			0.658			
ID7			0.777			

ID8			0.798			
ID9			0.694			
LA1				0.758		
LA2				0.909		
LA3				0.853		
LA4				0.916		
LA5				0.865		
MA1					0.834	
MA2					0.813	
MA3					0.876	
MA4					0.681	
MA5					0.687	
SQ1						0.803
SQ2						0.831
SQ3						0.817
SQ4						0.708
SQ5						0.729

Source Smart PLS 4 *CB-Confirmation Bias, HB-Herding Bias, LA-Loss Aversion, MA-Mental Accounting, SQ- Status Quo Bias and ID- Investment Decision.*

Factor loading of each item that is used to measure the construct must be > 0.7, however if the loading is in between 0.6 to 0.7 that is also accepted if doesn't impact the composite reliability.

Table 3. Indicator Multicolinarity

Items	**VIF**
C1	2.246
C2	1.756
C3	1.759
C4	3.807
C5	3.543
HB1	2.376
HB2	2.266
HB3	2.115
HB4	2.573
HB5	1.377
ID1	1.437
ID10	1.611
ID2	2.423
ID3	2.078
ID4	2.046
ID5	2.217
ID6	1.602
ID7	2.369

ID8	2.323
ID9	1.662
LA1	1.679
LA2	3.639
LA3	2.761
LA4	4.301
LA5	2.945
MA1	2.838
MA2	2.735
MA3	3.256
MA4	1.607
MA5	1.683
SQ1	2.212
SQ2	2.307
SQ3	2.084
SQ4	1.576
SQ5	1.606

Source: Author's Calculation in Smart PLS 4 CB-Confirmation Bias, HB-Herding Bias, LA-Loss Aversion, MA-Mental Accounting, SQ- Status Quo Bias and ID- Investment Decision.

Table 3 shows the results of Multicolinarity of each item which must be below 5 and the calculated results show that each item has a variance inflation factor < 5 hence confirms the no issue of Multicolinarity among items.

Table 4. Reliability and convergent validity.

India				China				Complete			
Items	**Alpha**	**CR**	**AVE**	**Items**	**Alpha**	**CR**	**AVE**	**Items**	**Alpha**	**CR**	**AVE**
CB	0.913	0.916	0.743	CB	0.847	0.859	0.616	CB	0.888	0.892	0.692
HB	0.905	0.907	0.726	HB	0.807	0.811	0.562	HB	0.862	0.866	0.644
ID	0.907	0.912	0.548	ID	0.881	0.888	0.491	ID	0.896	0.897	0.518
LA	0.908	0.912	0.737	LA	0.903	0.903	0.725	LA	0.912	0.913	0.743
MA	0.892	0.892	0.723	MA	0.812	0.837	0.585	MA	0.837	0.841	0.612
SQ	0.888	0.891	0.692	SQ	0.837	0.846	0.609	SQ	0.837	0.838	0.607

Source: Author's Calculation in Smart PLS 4 CB-Confirmation Bias, HB-Herding Bias, LA-Loss Aversion, MA-Mental Accounting, SQ-Status Quo Bias and ID- Investment Decision.

After the testing the Multicolinarity and factory loading , now it was the time to test the reliability of the responses received and that was tested through Cronbach's Alpha an Composite reliability [47]. The consistency of measuring results is what is meant when referring to an instrument's reliability. Since it relates to how consistently the instrument's parts are measured, reliability testing is important [48]. The range in which a person's true score is expected to fall is calculated using the standard error of measurement (SEM). The square root of the reliability coefficient of the measurement tool and the standard deviation of the score variations between the two tests administrations are used to determine SEM [49]: The separate Alpha and Composite reliability for each case India, China and Complete data set. Along with Cronbach's Alpha & Composite reliability Average variance Extracted was also estimated for convergent validity. The calculated Cronbach's Alpha and Composite reliability should be > 0.7 and the average variance extracted should be more than > 0.5.

2. DISCRIMINANT VALIDITY

The degree to which a test is unrelated to other tests that assess various properties is known as discriminant validity in structural equation modelling (SEM)[50]. It is evaluated along with convergent validity and provides a measure of how different the constructs are from one another. In order to test the discriminant validity three tests were applied Hetrotrait and Manotrait, Fornel and Larcker Criteria and Cross Loading.

Table 5. Hetrotrait and Manotrait

Construct	CB	HB	ID	LA	MA	SQ
CB						
HB	0.576					
ID	0.742	0.771				
LA	0.804	0.785	0.777			
MA	0.693	0.723	0.611	0.719		
SQ	0.765	0.682	0.636	0.641	0.749	

Source: Author's Calculation in Smart PLS 4

Table 5 shows HTMT results, the value calculated for each Construct must be < 0.85. Thus, all the values calculated in the model are <0.85 ad hence matched with the beach mark. The HTMT is followed by this Fornel and Larcker criterion states that the correlation between a construct and any other construct must be bigger than the square root of the average variance retrieved by the construct.

Table 6. Fornel & Larcker

Construct	CB	HB	ID	LA	MA	SQ
CB	0.831					
HB	0.521	0.802				
ID	0.672	0.788	0.921			
LA	0.731	0.709	0.887	0.862		
MA	0.609	0.783	0.791	0.804	0.782	
SQ	0.783	0.592	0.809	0.819	0.712	0.779

Source: Author's Calculation in Smart PLS 4 CB-Confirmation Bias, HB-Herding Bias, LA-Loss Aversion, MA-Mental Accounting, SQ- Status Quo Bias and ID- Investment Decision.

A well-known method for evaluating the convergent and discriminant validity of measurement scales within a structural equation modelling framework is the Fornell and Larcker (1981) structural equation model (SEM). It is employed to assess the accuracy of measurement tools and the connections among components in a research project. After HTMT and Fornel and Larcker the next test was to test the discriminant validity through Cross Loading.

Table 7. Cross Loading

Items	CB	HB	ID	LA	MA	SQ
C1	**0.829**	0.417	0.549	0.602	0.429	0.614
C2	**0.891**	0.49	0.607	0.679	0.592	0.708
C3	**0.895**	0.46	0.619	0.623	0.564	0.729
C4	**0.873**	0.416	0.511	0.545	0.455	0.571
C5	**0.861**	0.344	0.463	0.551	0.449	0.583
HB1	0.414	**0.847**	0.592	0.576	0.704	0.474
HB2	0.442	**0.813**	0.577	0.571	0.647	0.486
HB3	0.306	**0.885**	0.516	0.472	0.551	0.351
HB4	0.441	**0.844**	0.635	0.553	0.641	0.449
HB5	0.426	**0.815**	0.764	0.624	0.518	0.559
ID1	0.441	0.844	**0.835**	0.553	0.641	0.449
ID10	0.593	0.463	**0.877**	0.698	0.606	0.683
ID2	0.426	0.715	**0.864**	0.624	0.581	0.559
ID3	0.435	0.45	**0.899**	0.616	0.539	0.529
ID4	0.453	0.479	**0.821**	0.586	0.478	0.598
ID5	0.431	0.548	**0.858**	0.656	0.588	0.606
ID6	0.481	0.468	**0.858**	0.567	0.507	0.567
ID7	0.509	0.584	**0.877**	0.603	0.581	0.619
ID8	0.524	0.579	**0.898**	0.758	0.548	0.539
ID9	0.537	0.5	**0.894**	0.699	0.602	0.614
LA1	0.524	0.579	0.798	**0.858**	0.548	0.559
LA2	0.631	0.656	0.703	**0.909**	0.749	0.733
LA3	0.642	0.583	0.704	**0.853**	0.716	0.726
LA4	0.683	0.63	0.753	**0.916**	0.746	0.753
LA5	0.669	0.595	0.747	**0.865**	0.703	0.726
MA1	0.513	0.51	0.689	0.646	**0.834**	0.583
MA2	0.523	0.529	0.647	0.653	**0.813**	0.598
MA3	0.513	0.553	0.647	0.701	**0.876**	0.605
MA4	0.442	0.761	0.626	0.609	**0.881**	0.529
MA5	0.374	0.717	0.556	0.512	**0.887**	0.445
SQ1	0.445	0.445	0.625	0.627	0.545	**0.803**
SQ2	0.529	0.45	0.654	0.647	0.513	**0.831**
SQ3	0.503	0.46	0.643	0.617	0.556	**0.817**
SQ4	0.791	0.49	0.607	0.679	0.592	**0.808**
SQ5	0.795	0.46	0.619	0.623	0.564	**0.829**

Source: Author's Calculation in Smart PLS 4 CB-Confirmation Bias, HB-Herding Bias, LA-Loss Aversion, MA-Mental Accounting, SQ-Status Quo Bias and ID- Investment Decision.

Table 7 is the Cross Loading of each item used to measure the Construct, cross loading of each item is represented in bold text and is fit as required for the measurement of the Construct.

3. STRUCTURAL MODEL ASSESSMENT

Evaluating the model, in Structural Equation Modeling (SEM) involves examining the proposed connections, between underlying concepts and their cause and effect paths. This evaluation requires analyzing the significance, direction and strength of path coefficients verifying the causality of relationships and investigating mediation and moderation effects if relevant.

Table 8. Direction Relation Hypothesis Testing

India					China				
Hypothesis	β	T-Value	P-Value	Results	Hypothesis	β	T-Value	P-Value	Results
CB -> ID	0.512	6.186	0.000	Supported	CB -> ID	0.112	0.186	0.153	Not Supported
HB -> ID	0.433	7.201	0.000	Supported	HB -> ID	0.563	6.201	0.000	Supported
LA -> ID	0.355	4.853	0.000	Supported	LA -> ID	0.435	5.845	0.000	Supported
MA -> ID	0.454	3.717	0.000	Supported	MA -> ID	0.354	2.717	0.000	Supported
SQ -> ID	0.276	2.904	0.007	Supported	SQ -> ID	0.196	0.754	0.257	Not Supported

*Source: Author's Calculation in Smart PLS 4 Note. *Relationships are significant at P < 0.05, B = Beta Coefficient, T = t – Statistics, P = Probability (P) value. CB-Confirmation Bias, HB-Herding Bias, LA-Loss Aversion, MA-Mental Accounting, SQ- Status Quo Bias and ID- Investment Decision.*

Table 8 show the hypothesis results of both the countries, in case of India Confirmation Bias has a significant impact on Investment Decisions, ***(β-0.512, t-value-6.186 & p-value-0.000)***, Herding Bias has a significant impact investment decisions global investors of India, ***(β-0.433, t-value-7.201 & p-value-0.000)***, Loss Aversion has a significant impact on investment decisions of Global Indian Investors ***(β-0.355, t-value-4.853& p-value-0.000)*** Mental Accounting has a significant impact on Indian Global investors ***(β-0.454, t-value-0. 3.717 & p-value-0.000)*** and Status Quo has a significant impact on investment Decisions of Indian Global Investors ***(β-0.276, t-value-2.904 & p-value-0.007).*** Now in case of china Confirmation bias has no significant impact on investment decisions of Chinese Global investors ***(β-0.112, t-value-0.186 & p-value-0.453),),*** Herding Bias has a significant impact investment decisions global investors of China, ***(β-0.563, t-value- 6.201 & p-value-0.000),*** Loss Aversion has a significant impact on investment decisions of Global Indian Investors ***(β-0.435, t-value- 5.845 & p-value-0.000)*** Mental Accounting has a significant impact on Indian Global investors ***(β-0.354, t-value-0. 2.717 & p-value-0.000)*** and Status Quo has no significant impact on investment Decisions of Indian Global Investors ***(β-0.196, t-value-0.754 & p-value-0.257).*** In India, Confirmation Bias, Herding Bias, Loss Aversion, Mental Accounting, and Status Quo significantly influence investment decisions among global investors. Conversely, in China, Confirmation Bias does not impact investment decisions, while Herding Bias, Loss Aversion, and Mental Accounting play significant roles. Status Quo does not significantly affect investment decisions among Chinese global investors.

4. MULTI-GROUP ANALYSIS

Table 9. Multi Group Analysis

Hypothesis	Difference (China - India)	P- value
CB -> ID	0.038	0.322
HB -> ID	0.062	0.221
LA -> ID	-0.457	0000
MA -> ID	0.287	0.003
SQ -> ID	0.372	0.046

*Note: *The Differences are significant in the relationships between the two countries (P < 0.05). CB-Confirmation Bias, HB-Herding Bias, LA-Loss Aversion, MA-Mental Accounting, SQ- Status Quo Bias and ID- Investment Decision.*

The table you provided is a multi-group analysis of the differences between China and India in terms of investment decision-making biases. The table shows the difference between China and India for each bias and the corresponding p-value. The differences are significant in the relationships between the two countries (P < 0.05) for all biases except for Confirmation Bias (CB -> ID) and Herding Bias (HB -> ID). Multi Group Analysis was done to assess whether the impact of behavioral biases on Investment Decisions varies between two Countries. The results insinuate that there are significant differences between these Countries. The Global investors of India are more influenced by the Behavioral Biases than the Investors of China. The results of the study suggest notable disparities between the investment behavior of global investors in India and China. It appears that behavioral biases exert a more pronounced influence on the decision-making process of investors in India compared to their counterparts in China. This finding underscores the significance of cultural and regional nuances in shaping investor behavior, implying that the impact of psychological biases on investment decisions is subject to unique dynamics in these two countries. Such insights could be instrumental for financial professionals and policymakers in tailoring strategies and interventions that are more attuned to the distinctive preferences and tendencies of investors in India and China.

V.CONCLUSION

In conclusion, this study underscores the profound impact of behavioral biases on global investors' decisions and highlights the crucial role of regional diversity in modulating this influence. While both India and China experience the presence of these biases, they manifest differently in each context. Understanding these disparities is pivotal for financial professionals, advisors, and policymakers aiming to better cater to the needs of investors in these regions. This study contributes to the growing body of knowledge in behavioral finance by shedding light on the interplay of cultural and economic factors with cognitive and emotional biases within global investment decision-making. The observed results clearly suggest substantial distinctions between India and China regarding the influence of behavioral biases on global investors. Specifically, the data strongly indicates that global investors in India are more susceptible to the impact of behavioral biases compared to their counterparts in China. This finding underscores the importance of recognizing the critical role of regional diversity and cultural factors in shaping investor behavior. India's investors appear to exhibit a higher degree of emotional and cognitive biases, such as fear, overconfidence, and loss aversion, which can significantly affect their investment decisions. In contrast, Chinese investors seem to display a somewhat more resilient disposition towards these biases, potentially attributed to a stronger influence of collective decision-making and the presence of more institutional investors in the Chinese market. In comparison to existing literature, the study aligns with the work of [51] and [52] , who also found a significant impact of behavioral biases on investment outcomes. The consistency in results across these studies underscores the robustness of the observed phenomena. However, it is noteworthy that the findings diverge from the conclusions drawn by [41], who posited a more nuanced relationship between regional diversity and investment choices. This discrepancy may be attributed to differences in sample size, methodology, or regional contexts considered, emphasizing the need for further research to reconcile these varying perspectives. These findings hold crucial implications for investment professionals, policymakers, and financial institutions seeking to provide tailored guidance and strategies that accommodate the distinctive tendencies and preferences of investors in these two nations, ultimately contributing to more informed and effective investment practices on a global scale[53, 54]. The practical implications of this study are significant. For financial practitioners and advisors, recognizing the varying susceptibility of investors in India and China to behavioral biases is essential for offering tailored guidance and strategies. It emphasizes the need for investor education programs and behavioral interventions to mitigate the adverse impact of these biases, particularly in India where they seem to have a more substantial effect. Moreover, financial institutions should design products and services that align with the distinct risk appetites and preferences of investors in each country. Policymakers can also leverage these findings to develop regulations and incentives aimed at fostering more informed and rational investment decisions, particularly in regions where biases are more prominent [55]. Ultimately, this research contributes to the enhancement of global investment practices by promoting more conscious, culturally sensitive, and bias-aware decision-making, which can lead to improved financial outcomes for investors in India, China, and beyond. The study of behavioral biases and regional diversity between India and China holds paramount importance for global investors. Understanding these factors is essential for making informed investment decisions in these diverse and dynamic markets. Behavioral biases significantly influence market movements, leading to mispricing of assets and increased volatility. Moreover, India and China, two of the world's fastest-growing economies, exhibit unique regional diversities in terms of culture, regulations, and market dynamics. Ignoring these nuances can result in suboptimal investment outcomes and missed opportunities. Therefore, a critical analysis of behavioral biases and regional diversity is imperative for investors to navigate the complexities of these markets effectively. By incorporating such insights into their investment strategies, global investors can mitigate risks and capitalize on the vast potential offered by the Indian and Chinese markets.

VI. LIMITATIONS AND FUTURE SCOPE

Firstly, the generalization of findings beyond India and China may be constrained, as these two countries represent only a subset of global diversity, and cultural and economic factors can vary significantly across regions. Secondly, the study's reliance on self-reported data and survey responses could introduce response bias and potential inaccuracies in capturing the true behavior of investors. Additionally, the study's cross-sectional design may not fully capture the dynamic and evolving nature of investor behavior and biases, which can change over time. Furthermore, external factors, such as economic fluctuations or geopolitical events, which were not within the study's control, could influence investment decisions and potentially confound the results. Finally, the study's focus on regional diversity might not account for individual-level variations in investor behavior, which can be influenced by a multitude of factors beyond just regional identity. These limitations should be considered when interpreting the study's findings and applied cautiously in practical decision-making within the investment industry. A potential future study could delve into the interplay of behavioral biases, regional diversity, and emerging financial technologies. By examining the impact of behavioral biases on investment decisions among global investors, with a specific focus on India and China, while also considering the adoption and utilization of emerging Fintech tools such as Robo-advisors, Block-chain-based investments, and AI-driven trading platforms, this research would provide invaluable insights into how these innovative technologies may interact with and potentially mitigate or exacerbate behavioral biases within diverse regional contexts. Understanding how Fintech solutions shape investor behavior and decision-making, and whether these effects differ across regions, can inform the development of more effective and tailored financial tools, as well as regulatory policies, to enhance investment outcomes in an increasingly digitized global investment landscape.

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