ASSESSING THE INFLUENCE OF PSYCHOLOGICAL BIASES AND RISK TOLERANCE ON INVESTMENT DECISION-MAKING USING STRUCTURAL EQUATION MODELING

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ABSTRACT:
Investment decision-making is a complex process influenced by many psychological and behavioral factors. This study aims to assess the influence of psychological biases, specifically overconfidence, loss aversion, herding behavior, anchoring, and individual risk tolerance, on investors' decision-making processes. Drawing on behavioral finance theory, the research employs Structural Equation Modeling (SEM) to examine the interrelationships between these constructs using primary data collected from a sample of individual investors. The findings mainly focus on psychological biases, followed by risk tolerance, which plays a vital role in shaping investment behavior. Overconfidence and herding tendencies have strong positive effects, meaning risk tolerance should be moderate and contain biased behavior relationships. This study mainly focused on the financial advisors and policy makers to consider the behavior dimension when designing investment strategies, along with educational interventions. Also, enhanced the investor awareness through explaining suboptimal decisions.

Keywords: Psychological Biases, risk tolerance, Investment decision making, behavioral finance, SEM, overconfidence.

I.INTRODUCTION

Psychological biases mainly focus on irrational decision-making characteristics, such as cognitive bias, self-attribution, and overconfidence. The main psychological factors that affect various factors include social influence, fear of missing out, overconfidence, and herding Behavior. It has a positive impact on investment decision-making.[8]. Here, psychological biases are included in decision making as loss aversion bias, which shows that the investor experiences the emotional effects of losing money and is satisfied with achieving a gain.[9] Cognitive bias leads to investors holding and declining investments longer than rational economic decisions dictate. Conventional economic theories presume that investors act rationally and frequently fail to explain investor behavior in the dynamic financial market environment.[10]. Recently, the field of behavioral finance has emerged, which has helped to clarify the substantial impact of individual variances and psychological aspects on monetary decision-making.[11] Cognitive and emotional biases frequently influence investors, causing them to make less-than-ideal decisions. [12].Psychological biases, including anchoring, herding, overconfidence, and loss aversion, are well-known and significantly impact investment choices.[13]. Along with these biases, risk tolerance, or the extent to which an investor is prepared to tolerate return fluctuation, is a critical factor in determining financial behavior.[13]. Depending on one's personality, level of financial literacy, and life events, one's risk tolerance can either exacerbate or alleviate the impact of cognitive biases while making decisions.[14].

More empirical research needs to use strong analytical approaches to examine how psychological biases and risk tolerance interact, while interest in these behavioral components is rising.[17]. Structural Equation Modeling (SEM) is a strong multivariate technique that this study uses to fill that void by investigating the intricate interactions between these concepts. [14]. The structural patterns impacting investment decisions can be better understood using SEM, which allows for the simultaneous investigation of many dependent connections.[19]. This research aims to grasp better the psychological foundations of investor behavior, which can benefit financial advice practices, investor education, and behavior-based investing models.[7].

1.1 KEY CONTRIBUTION

- It mainly focuses on a comprehensive model that examines the multiple psychological biases, including overconfidence, loss aversion, anchoring, and risk tolerance. It also provides a holistic approach to understanding the behavioral factors influencing investment decision-making.
- SEM analysis provides empirical ideas related to the relationship among the psychological variables, followed by investment behavior, allowing for greater analytical ideas related to traditional regression techniques.
- The findings mainly focused on investors, financial advisors, and policy makers and defined how the specific bias helps shape investment choices and potentially improves decision-making strategies.

The following sections cover this research paper: Section I describes the Introduction, which explains the main concepts of the particular research. Section II describes the Literature review, which consists of previous research followed by the various concepts of decision making, risk tolerance, and psychological biases. Section III explained the research model, the Hypothesis statement, and the Materials and methods. Section IV describes the results and discussion, followed by SEM, Demographic information, SEM analysis for psychological biases, Decision making and financial risk, scale reliability, and construct reliability. Section V describes the Discussion and findings. Section VI summarizes the main key findings and results.

II. LITERATURE REVIEW

The term "availability bias" describes the tendency for investors to rely on readily available information instead of thoroughly investigating all pertinent factors. Consequently, the focus on current events runs the risk of distorting the true character of the investment. People tend to make hasty financial decisions due to self-control bias, which is characterized by the need for rapid pleasure. Investors prone to the overconfidence bias have a tendency to exaggerate their abilities while downplaying the risks associated with investing.[1]. Prejudice refers to investors' tendency to hold on to assets despite poor results. In contrast, the illusion of control bias describes their perception that they have more control over outcomes than they actually do. Being biased means being prone to make assumptions without all the facts rather than relying on specific examples. Discoveries have shown that EB is a robust predictor of rational decision-making in various domains, one of which is financial decision-making. [20]. Behavioral biases are thought to have less of an effect on investing decisions when using ES because it places more emphasis on facts and less on emotions (Kohler et al., 2019). The author explains that the decision-making process is really a collection of smaller processes that come together to form the final product (Harikanth & Pragathi, 2012). The objective is to determine the intended return and investigate potential alternatives; this is where the process starts. After that, they weigh the pros and cons of each choice and choose the one with the lowest price tag (Shefrin, 2002). [2]. Two popular rational methods advocated by modern economists use the expected utility theory to make investment decisions and accurate predictions. Milton Friedman, a famous economist, said that putting people in charge of the financial markets would make them what they are today. He stressed that market participants are not allowed to use reasoning. Consequently, considering the importance of human behavior led to a shift from a traditional approach to decision-making to a more contemporary perspective. That shows how much faith investors put in their opinions and how little they value facts and information.[12].

Rajabat Ali (2023) was one of the authors who discussed one of the more well-known psychological biases that has an enormous effect on investors' decisions, which is AB. People rely largely on the first piece of information because of this cognitive bias (Shin & Park, 2018). Anchors frequently buy stocks based on their most recent high price rather than observing it objectively. Because of this bias, investors base their decisions on how prices are currently moving (Singh, 2016). [3]. This effect is most clearly seen when one goes shopping and uses the price of a desired handbag as a benchmark against which to evaluate all of the other handbags. You would consider the second handbag to be inexpensive if its value was $800, even though the first one cost $1,000. [6].

Investors fall prey to this bias when they consider the information to be easily accessible rather than exploring other options. [21]. Both the content and reliability of the data used to make decisions have a major influence on those people (Barber & Odean, 2001).[4]. When weighing the potential rewards against the possible losses, most investors waver between potential investments. Investors' tastes are always evolving in response to new information.[22]. Consequently, investors are known to factor in established patterns, regardless of how faulty or untrustworthy the underlying data may be. In a similar vein, investors become nervous and jump to conclusions when a company in the financial market admits misconduct (Chen & Tsai, 2010).[5].

III. RESEARCH MODEL

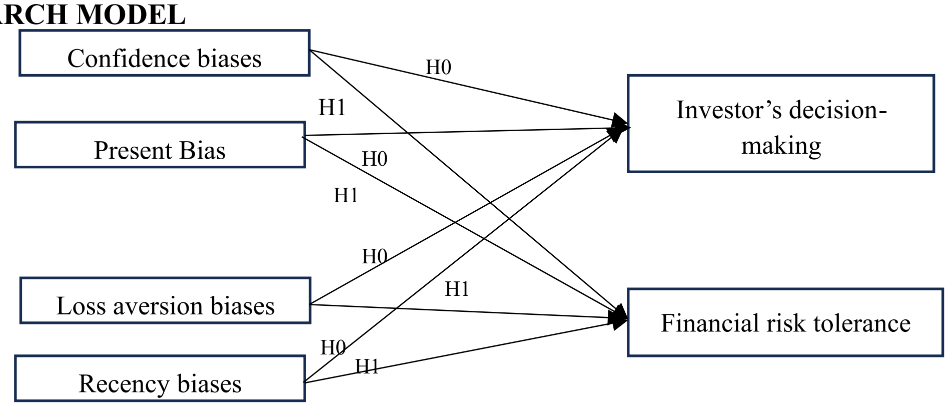

Fig: 1: Research Model for Conceptual Framework

To interpret above fig 1 depicts a theoretical framework that describes the interplay between psychological biases, decision-making style, and the capacity to tolerate financial risk when making investing decisions. As a whole, psychological biases are comprised of four main parts, which the model breaks down as follows: loss aversion, short-termism, recency bias, and anchoring bias. When people let their biases influence their decision-making, it shows up in their financial choices. Handling financial risk is another factor influencing investing choices and functions as a parallel predictor. The interplay between cognitive risk evaluations and behavioral and emotional elements is emphasized in this paradigm, which in turn influences investor behavior.[10].

3.1 HYPOTHESIS STATEMENT

H0: (Null Hypothesis): There is no significant influence of psychological biases and risk tolerance on investment decision-making.
H1: (Alternative Hypothesis): There is a significant influence of psychological biases and risk tolerance on investment decision-making.

3.2 MATERIALS AND METHODS

All statistical analyses for this study were based on data obtained from a pilot study with 400 participants. The correlation between the study's independent variables was laid bare by the findings. Reliability testing is necessary since it affects the uniformity of a measurement device's components. The Cronbach's Alpha coefficient is a famous internal consistency metric. Furthermore, when utilizing Likert scales, it is thought to be the most suitable reliability metric. A measurement's 65 dependability is the extent to which it consistently and reliably produces results. Consistency in the data obtained and generalizability of the outcomes depend on measuring the data's reliability through analysis. A dependability test was done on the scale's internal consistency using sample data from the pilot study. Each construct exceeded the minimum cutoff value (Cronbach's α-value = 0.70) in terms of Cronbach's alpha. In keeping with the goals of this study, the final scale underwent revisions to ensure it was suitable for responders. Government reports, departmental records, census data, and other secondary sources are examples of what is known as secondary data. When compared to primary data, it is both cheaper and easier to work with. Study measuring tools rely heavily on secondary data since it aids researchers in defining research challenges and creating successful instruments. This study administered a questionnaire to investors in order to learn how their biases affect their financial risk tolerance and decision making. Methods include conducting semi-structured interviews and close-ended surveys on a 5point Likert scale for easy data analysis. An investor demographic profile and information pertaining to the study's aims are the two sections of the questionnaire. The researcher makes sure that all the chosen investors receive the survey to collect reliable data for the study. In order to gather information regarding Technology Business Incubators, a survey tool is utilized. When choosing a survey instrument, it is essential to keep in mind that it needs to be able to measure the variable accurately, among other things. Likert scale analysis should form the basis of the survey instrument, which should also meet the criteria for reliability and validity. Researchers should ensure that the survey questions they use are relevant to the study's goals and objectives to ensure validity and reliability, which is the degree to which they believe the research instruments are accurate.

Table 1: Latent Constructs and Observed Items

Latent Variable	Research Questionnaire	Factor Value	AVE
Psychological Biases	PB-1 For some reason, I can't help but dwell on financial market data from the past.	2.02	1.862
	PB-2 I stray from my financial intentions by making investing selections with a short time horizon.	1.97	
	PB-3 I base my financial selections on current events, with the expectation that they will persist into the future.	1.98	

	PB-4 In times of sharp market declines, I stay out of the stock market.	1.82	
	PB-5 I care more about results in the near term than in the far future.	1.52	
Decision Making	DM-1 My intuition and first impressions are always right when it comes to making investments.	1.88	1.908
	DM-2 When I invest, I usually go with my gut.	1.85	
	DM-3 When an investment opportunity presents itself, I go with my gut.	1.99	
	DM-4 Having a logical justification is less important than having a gut feeling when it comes to making investments for me.	1.86	
	DM-5 I typically go with my intuition when making financial investments.	1.96	
Financial Risk Tolerance ability	FRTA-1 When it comes to investing in stocks and stock mutual funds, I am more at ease.	1.98	1.972
	FRTA-2 As far as I'm concerned, I'm a real risk-taker.	1.95	
	FRTA-3 I expect a large return on my investments, I am willing to face significant risks.	1.98	

	FRTA-4 If you could invest all of your money over, would you be ready to take a bigger risk?	1.97	
	FRTA-5 I propose allocating Rs. 10,000 among three types of investment instruments: 60% lowrisk, 30% medium-risk, and 10% high-risk.	1.98	

To interpret Table 1, respondents exhibited moderate psychological biases (1.862) according to the research questionnaire's factor values; this suggests that they tend to rely on previous data and think in the short term, with less weight given to immediate consequences (lowest at 1.52). With an average factor value of 1.908, decision-making is heavily biased toward gut feelings and intuition, as seen in DM-3 (1.99) and DM-5 (1.96). Respondents appear to be at ease taking investment risks, as indicated by the consistently high values across all items (usually 1.95-1.98), with the highest average factor value of 1.972 in financial risk tolerance capacity. These numbers show that people are quite open to taking financial risks and making decisions based on intuition, even when they are susceptible to psychological distortions.

IV. RESULTS AND DISCUSSION

4.1 STRUCTURAL EQUATION MODELING

Structural Equation Modelling, or SEM, is a statistical method for exploring and understanding the connections between hidden and visible factors. It is comparable to regression analysis in that it studies linear causal relationships between variables, but is far more effective because it accounts for measurement error. SEM is more of a method for verifying existing theories than creating new ones.[15]. The SEM analysis consists of multiple regression equations. SEM analysis should have various benefits in comparing the multiple regression model, which recognizes the interdependencies to transform the dependent variable through a multiple regression equation of independent variables. This also makes it possible for independent factors to simultaneously impact dependent variables, which helps identify direct and indirect influences on the dependent variable. Statistical equation modeling (SEM) means that the studied causal processes can now be represented graphically by a collection of structural (i.e., regression) equations. To test the hypothesis model with a comprehensive analysis, which provides the relationship between the variables. Which is used for to determine the data should be fit. If the value of goodness of fit is satisfactory, the result is the hypothesized relationship between the variables.[16].

4.2 DEMOGRAPHIC PROFILE AND RESPONDENTS

Table: 2: Demographic Information

Demographic Data		Frequency	
Demographic Profile	Type	Number	Percentage (%)
Age Group	Between 26-33	98	24.5

	From 34-41	127	31.75
	42-49	86	21.5
	above 50	89	22.25
Gender	Male	206	51.5
	Female	194	48.5
Qualification	Bachelors	157	39.25
	Masters	125	31.25
	Professionals	118	29.5
Experience level	1-3 Years	56	14
	4-6 years	162	40.5
	Maximum of six years	182	45.5
Disposable Income	below 45,000	89	22.25
	45001 - 65,000	97	24.25
	65,001 - 85,000	24	6
	85,001-1,05,000	96	24
	Above 1,50,000	94	23.5
Annual Savings	Less than 1,00,000	217	54.25
	1,00,001-3,00,000	96	24
	Above 3,00,000	87	21.75
Invested Savings Percentage	Less than 10%	96	24
	Between 10%-20%	91	22.75
	Between 21% -30%	117	29.25
	Above 30%	96	24
Occupation	Business	73	18.25
	Private Sector	187	46.75
	Millennials	140	35

(Source: Author calculations)

The above Table 2 describes the respondent's information, which helps analyze the investment decision-making influenced by psychological bias, followed by risk tolerances. In terms of age, the largest segment is 31.75%, followed by the group of 34-41. 24.5% of the respondents were noted as 26-33 years old, indicating a significant portion of the respondents are working years. Here, the respondent age group is mentioned as 42-49, and above 50% is noted as having life experience that influenced financial behavior based on Gender distribution, noted as 51.5% of people as females and 48.5% as males. Compared to both, we have to analyze the balanced relationship between both genders. Followed by qualifications, most respondents noted a bachelor's degree as 39.25%, a Master degree as 31.25%, and a professional degree as

29.5%. These indicate they are well-educated and make informed investment decisions. Based on experience level, which is noted as the most of the respondents indicate as moderate to work experiences with 45.5% having 6 years, 40.5% have 4 to 6 years. 14% noted as 1-3 years. Followed by the income status level, 24.25% of people earned between 45001 and 65000 monthly, which means some earnings followed by 85,001 to 1,05,000 and 1,50,000. Comes under the annual savings more than half of the respondents are saved less than 1,00,000 with 24% followed by 1,00,001 to 3,00,000. Compared to all values, which are all reflected in the tendency among the lower savings levels related to good income brackets. After evaluating the demographic information reflected in the composition, it is determined that it varies according to experience, income level, and savings. These characteristics provide a positive relationship for exploring the psychological biases, risk tolerance, and investment decision-making used by SEM.

4.3 SEM ANALYSIS FOR PSYCHOLOGICAL BIASES

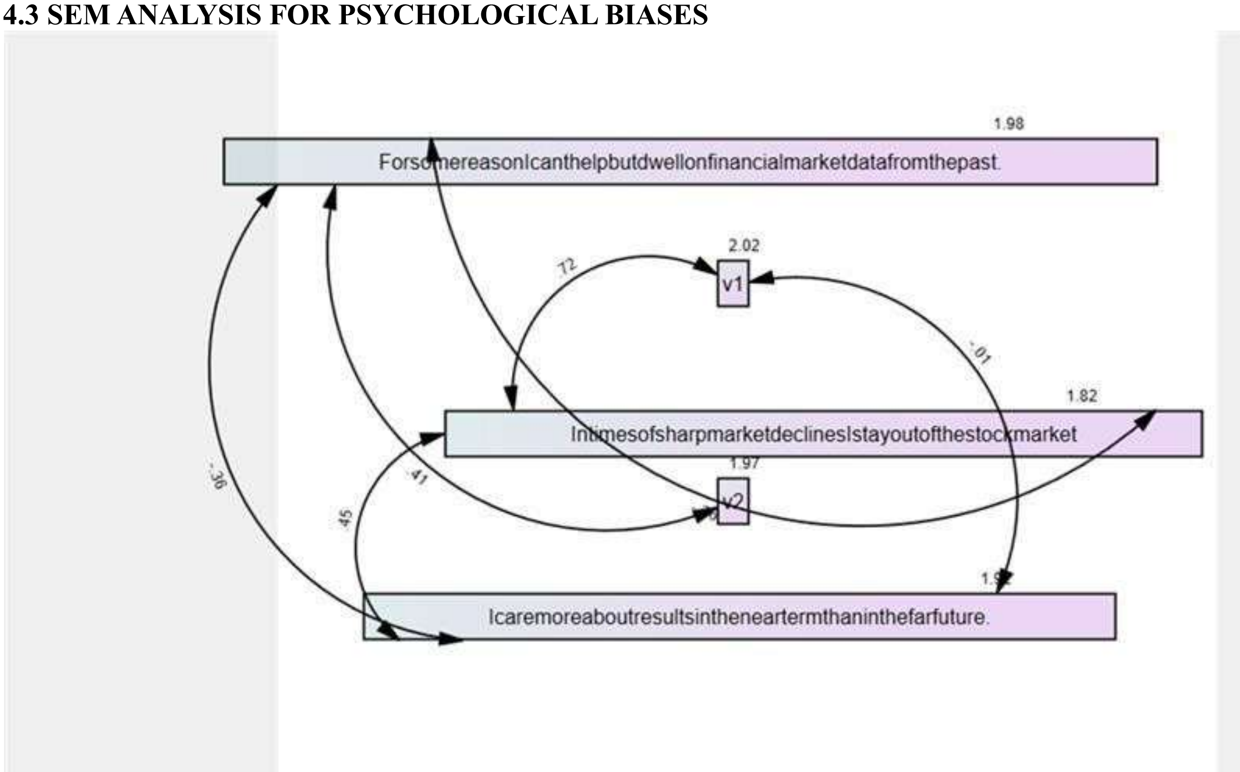

Fig:2 SEM Analysis for Psychological Biases

To interpret the fig 2, the Analysis of psychology describes the relationship between the three behavioral statements followed by market behavior. In this, the two types of latent variables are also mentioned as V1 and V2. The arrow relationship represents the influence of those variables. Numerical values represent the path coefficients. Based on the analysis, V2 is mentioned as 1.97, which provides a strong relationship loaded by the factor values. After evaluating the overall structure, it is evident that the observable variables and behaviors are interconnected and influenced through psychological constructs.

4.3.1 MODEL FIT SUMMARY

Table: 3 Output Summary of CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model (DM)	11	39.479	4	.000	9.870
Saturated model (SM)	15	.000	0		
Independence model (IM)	5	154.098	10	.000	15.410

Based on table 3 describes the model fit statistics, the default model is statistically significant with a Chi-square value (CMIN) of 39.479, 4 degrees of freedom (DF), and a p-value of.000. However, the p-value also indicates poor model fit, as ideally, a non-significant p-value (>0.05) is preferred. An additional indication of a match is the CMIN/DF ratio of 9.870, significantly higher than the generally accepted criterion of 3 or less. As predicted, the saturation model exhibits a perfect match (CMIN = 0, DF = 0), unlike the independence model's dismal performance (high Chi-square value: 154.098, CMIN/DF: 15.410). The default model fits the data better than the independence model, but it still doesn't meet the standards for a good model fit, so something must be done to improve it. The default model exhibits a Chi-square (CMIN) value of 39.479 with 4 degrees of freedom and a p-value =0.000, testing the hypothesized correlations among psychological biases, risk tolerance, and investment decision-making. Because the p-value is smaller than 0.05, we may reject the null hypothesis (H_0) and say that the model is statistically significant. This lends credence to the null hypothesis (H_1), which states that psychological biases and risk tolerance substantially impact investment decisions. While the significance does lend credence to H_1, the 9.870 CMIN/DF ratio (much exceeding the allowed threshold of 3) suggests a decent fit for the model, suggesting that even while the association is statistically significant, the present model might not fully represent the data's structure.

Table: 4 Output Summary of RMR and GFI

Model	RMR	GFI	AGFI	PGFI
DM	.187	.964	.865	.257
SM	.000	1.000		
IM	.303	.869	.803	.579

To interpret Table 4, the default model appears to have a relatively good fit, according to the fit indices. A comparatively high Root Mean Square Residual (RMR) score of.187 suggests that there is a mismatch between the actual and expected values. There is a good fit indicated by the Goodness-of-Fit Index (GFI) of.964, which is near to 1, and by the Adjusted Goodness-of-Fit Index (AGFI) of.865, both of which are within an acceptable range (≥0.80). With a PGFI of.257, the model is either very simple or there is little parsimony. The default model shows a better fit than the independence model, but there is still room for improvement, particularly in residual error and model parsimony. In contrast, the saturated model should show about the fit as perfect, which contains the value as RMR as 0.000, GFI as 1.000. Independence values as fit means followed by RMR as 0.303, GFI as 0.869, and AGFI as 0.803. Followed by the above interpretation which is accepted by the criteria as 0.80, the default model of goodness of fit index as 0.964., AGFI as 0.865. Which is provides the result of overfitting. Followed by the model complexity, Parsimony

Goodness of fit index (PGFI), as 0.257, which is also satisfactory, indicating a moderate level. To mention the lower fit indices as RMR as 0.303, GFI as 0.869, and AGFI as 0.803, the independence model is the default accuracy model. The results show that the null hypothesis (H0) is rejected, indicating the independence of the model is significantly acceptable, as evidenced by the GFI and AGFI. Here is evidence related to the alternative hypothesis (H1) that suggests psychological biases. It also impacts investment decision-making. Evaluate all metrics to help improve the high level of RMR and PGFI.

Table : 5 Output summary of Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
DM	.400	.298	.302
SM	.000	.000	.000
IM	1.000	.000	.000

To interpret Table 5 , we noted that a moderate amount of model parsimony is suggested by the parsimony fit indices for the default model. The Parsimony Ratio (PRATIO) stands at.400, suggesting that 40% of the potential degrees of freedom are being utilized. This indicates that the trade-off between model complexity and fit is reasonable. Although the model does have some fit, it does not attain high parsimony-adjusted fit, as indicated by the comparatively low Parsimony Normed Fit Index (PNFI) of.298 and the Parsimony Comparative Fit Index (PCFI) of.302. According to popular consensus, values closer to or above 0.50 are acceptable. The saturation model fits the data well, but has no degrees of freedom. Therefore, these indices have zero values. The independence model, on the other hand, is maximally parsimonious but provides a terrible fit (PNFI and PCFI = 0). The default model shows a compromise between model complexity and fit, although there is potential for improvement in terms of parsimonious fit, as indicated by the low PNFI and PCFI values. A moderate amount of model parsimony is shown by the default model's Parsimony Ratio (PRATIO) of 0.400, which means that 40% of the available degrees of freedom are being used. Both the Parsimony Normed Fit Index (PNFI) and the Parsimony Comparative Fit Index (PCFI) are low, at.298 and.302, respectively. Values greater than or equal to 0.50 are typically considered ideal. According to these principles, the model does explain some variation in investment decision-making behavior, but its explanatory ability is low compared to its complexity. With its optimal parsimony (PRATIO = 1.000) and lack of meaningful fit (PNFI and PCFI = 0), the saturation model has zero values by definition, and the independence model is equally flawed. In contrast, the default model strikes a better balance between model fit and simplicity. The default model provides sufficient evidence to reject the null hypothesis (H_0) when other fit indices (such as a substantial chi-square and good GFI/AGFI) are taken into account, even though the PNFI and PCFI values are low. The results show that psychological biases and risk tolerance play a big role in investment decision-making, which supports the alternative hypothesis (H_1). However, the model might be improved to make it more parsimonious and fit better.

Table: 6 Output Summary of RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
DM	.149	.109	.193	.000

IM	.190	.164	.217	.000

To interpret Table 6, which shows about the RMSEA of.149, the default model is not well-fitting; this value is higher than the tolerable cutoff of 0.08. The range of the 90% confidence interval is from 0.109 to 0.193, which further supports the idea that the actual RMSEA value is likely to be within that range and still shows a good fit. Furthermore, the PCLOSE value of 0.000 indicates that the close fit hypothesis (RMSEA ≤ 0.05) is not supported, proving that the fit is Good. The independence model is much less successful; it has a PCLOSE of 0.000, a confidence interval ranging from 0.164 to 0.217, and an RMSEA of 0.190. To summarize, the default model outperforms the independence model in terms of fit, but there is still plenty of opportunity to enhance its overall performance according to its RMSEA and associated statistics. A Good model fit is indicated by the default model's RMSEA score of 0.149, which is significantly higher than the tolerable threshold of 0.08. Even the lower bound is higher than acceptable levels, as confirmed by the 90% confidence interval (LO 90 = 0.109, HI 90 = 0.193), further confirming the good match. Also, the model does not fit the data very well; the PCLOSE value is 0.000, which means that the null hypothesis that the RMSEA is less than or equal to 0.05 is rejected. In contrast to the default model's improved performance, the independence model's even lower performance (RMSEA= 0.190) shows that neither model achieves the target level of fit. The default model still shows a significant relationship between psychological biases, risk tolerance, and investment decisionmaking, so we can reject the null hypothesis (H_0) and accept the alternative hypothesis (H_1), even though there is a poor fit. This is supported by significant chi-square results and good GFI/AGFI values from previous metrics. The model needs to be refined or re-specificity to increase its overall fit and validity because of the high RMSEA.

4.4 SEM ANALYSIS FOR DECISION MAKING

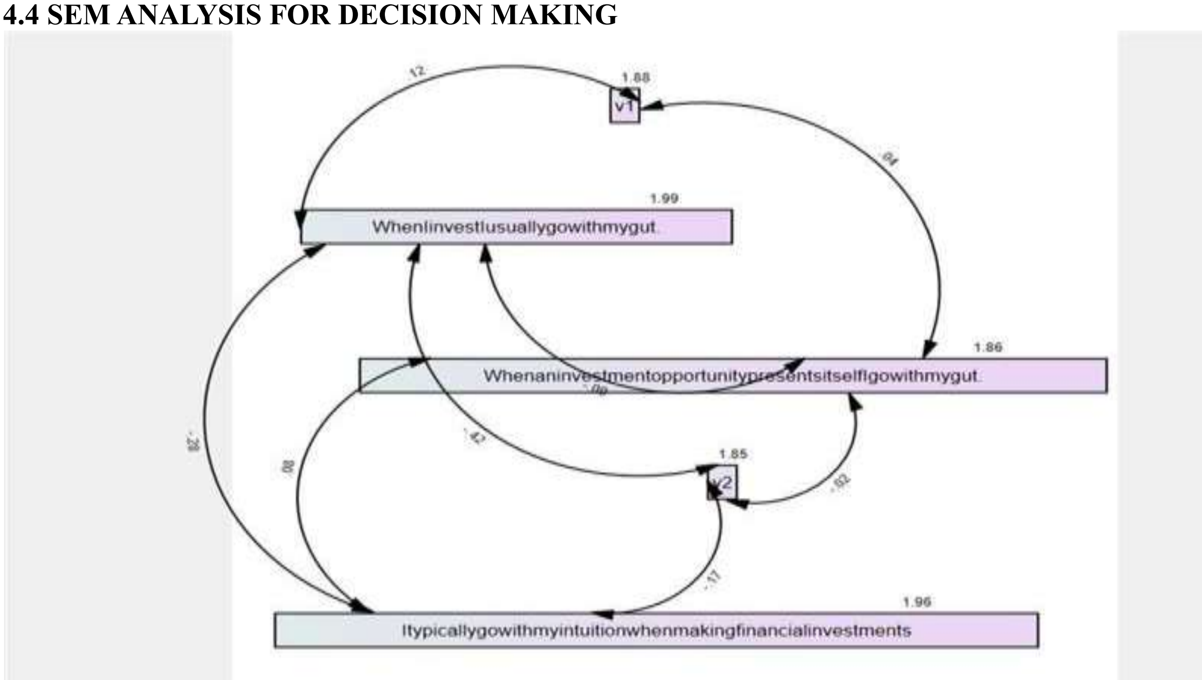

Fig:3 Sem Analysis for Decision Making

To interpret fig 3 structural equation model (SEM) depicted here investigates how gut feelings affect investment returns. The three behavioral assertions that revolve around "going with my gut" when investing is loaded onto two latent variables, v1 and v2. There is a substantial correlation between these claims and the latent components, as shown by the strong standardized path coefficients (varying from 1.85 to 1.99). The fig 3 implies that v1 and v2 capture aspects of affect driven or intuitive investing behavior, which is characterized by people making financial decisions based on intuition or gut feelings rather than logical reasoning.

4.4.1 MODEL FIT SUMMARY

Table: 7 Output summary of RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
DM	.000	.000	.073	.868
IM	.085	.058	.114	.019

To evaluate Table 7, define the default model's RMSEA of.000, which is significantly lower than the cutoff of 0.08, indicating a very good match to the data. All points on the 90% confidence interval (LO 90 = 0.000, HI 90 = 0.073) fall within acceptable ranges, suggesting that the actual RMSEA is probably near zero. The null hypothesis that the RMSEA is less than or equal to 0.05 cannot be rejected because the PCLOSE value of 0.868 is significantly higher than the usual threshold of 0.05. It appears that the model accurately represents the data and has a good fit. Independent variables, on the other hand, have RMSEAs of.085 and confidence intervals (LO 90 = 0.058, HI 90 = 0.114) that are greater than the acceptable level of 0.08. The independence model does not adequately account for the data, as there are large disparities between the actual and expected results (PCLOSE = 0.019). These results present strong evidence that the null hypothesis (H_0) should be rejected, as the default model shows a significant and close match, which supports the alternative hypothesis (H_1). This provides more evidence that people's risk tolerance and psychological biases play a major role in their investment decisions.

Table:8 Output summary of AIC

Model	AIC	BCC	BIC	CAIC
DM	26.719	27.117	78.576	91.576
SM	30.000	30.459	89.834	104.834
IM	48.852	49.005	68.797	73.797

One technique to table 8 evaluate the fit of various models while considering model complexity is with the use of the AIC, BCC, BIC, and CAIC, which stand for Consistent Akaike Information Criterion, Bayesian Consistent Criterion, and Bayesian Information Criterion, respectively. With lower values for all criteria (AIC = 26.719, BCC = 27.117, BIC = 78.576, and CAIC = 91.576), the default model shows the best fit compared to its complexity. As shown by these values, the default model achieves a satisfactory compromise between model fit and parsimony. Saturated models are more complex and reflect a perfect match; yet, they have higher values for all criterion (AIC = 30.000, BCC = 30.459, BIC = 89.834, CAIC = 104.834), indicating that they are less efficient even if they fit the data exactly. With the highest values across all criterion (AIC = 48.852, BCC = 49.005, BIC = 68.797, CAIC = 73.797), the independence model which has poor fit is clearly the worst option. The default model's superior performance on these indices suggests that psychological biases and risk tolerance play a considerable role in investing decision-making, lending credence to the rejection of the null hypothesis (H_0). Hence, these characteristics significantly impact investment decisions, as the results support the alternative hypothesis (H_1).

Table: 9 Output Summary of HOELTER

Model	HOELTER .05	HOELTER .01
DM	3317	5099
IM	188	238

To interpret table 9, In terms of sample size and degrees of freedom, the Hoelter index gives a measure of model fit. Maximum sample sizes that guarantee model stability at the 5% and 1% significance levels, respectively, are represented by the two critical values given, HOELTER.05 and HOELTER.01. With HOELTER.05 at 3317 and HOELTER.01 at 5099 both significantly higher than the actual sample size and the assumption that it is considerably smaller the default model appears to be stable and has a large enough sample to produce credible findings. The model is consistent at both common significance levels, and these numbers show that it is not over fitted.
The independence model, in contrast, reveals significantly lower Hoelter values: 188 for HOELTER 0.05 and 238 for HOELTER 0.01. These numbers suggest that the independence model is not stable enough to be relied upon at the 5% and 1% levels of significance, respectively, given the size of the sample. This indicates that the data are not well-suited to the independence model since it fails to capture the interplay between psychological biases, risk tolerance, and investment choices. These results provide further evidence to reject the null hypothesis (H_0) and accept the alternative hypothesis (H_1), considering the stability of the default model and the instability of the independence model, respectively. This suggests that individuals' risk tolerance and psychological biases play a big role in investment decisions, and that the default model better captures the facts.

4.5 SEM ANALYSIS FOR FINANCIAL RISK

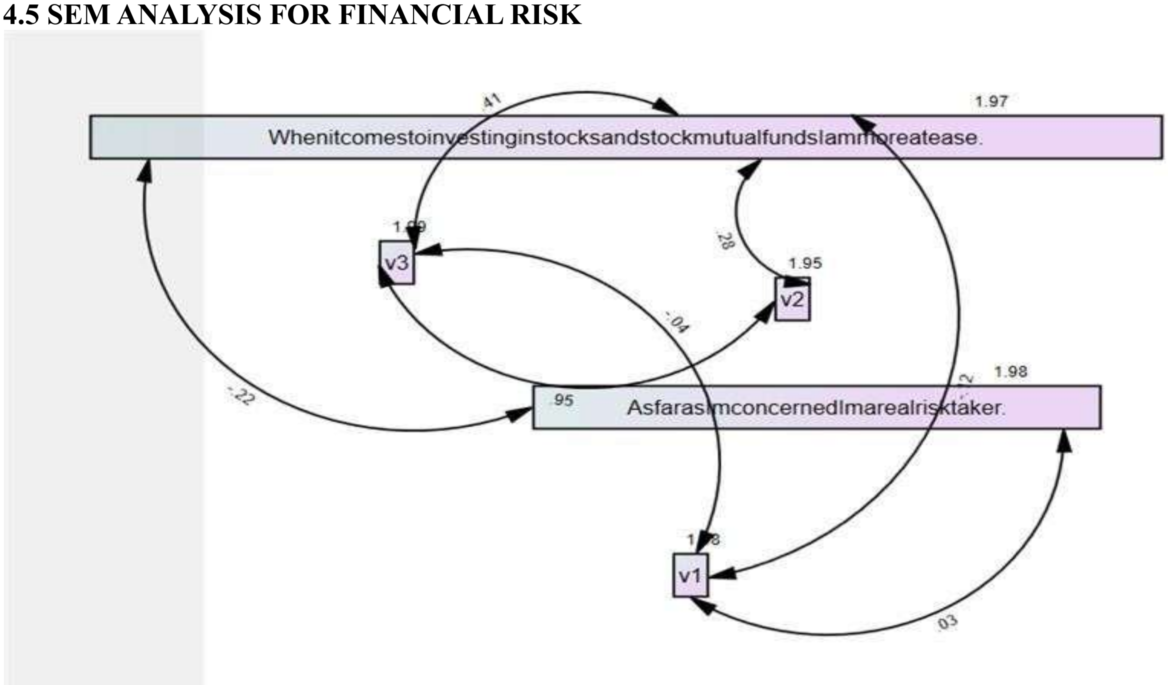

Fig:4 SEM Analysis for Financial Risk

To interpret fig 4 describes the structural equation model (SEM) delves at the mental aspects connected to the act of taking financial risks. Two assertions have been noted: one is about being comfortable with stock/mutual fund investments, and the other is about identifying as a risk-taker. The statements have high standardized coefficients (1.95-1.98), which indicates a strong association with underlying attitudes toward risk and confidence in financial decision-making. They heavily load onto three latent variables (v1, v2, and v3). An individual's risk tolerance is a key component impacting their comfort level when making investment decisions, according to the interactions between latent variables (e.g., v1 to v2 and v3) and the route from taking risks to feeling at ease.

4.5.1 MODEL FIT SUMMARY

Table: 10 Output summary of CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
DM	12	10.566	3	.014	3.522
SM	15	.000	0		
IM	5	138.716	10	.000	13.872

To evaluate the table 10 mentioned the model fits and assistance for hypothesis evaluation are provided by the Chi-square test (CMIN) results. With three degrees of freedom (DF) and a p-value of.014, the default model's Chi-square (CMIN) value is 10.566, which is lower than the 0.05 criterion. It follows that the default model is statistically significant, allowing us to reject the null hypothesis (H_0). A CMIN/DF ratio of 3.522 is within the suitable range (below 5), indicating that the model's level of complexity is commensurate with its fit. On the other hand, saturated models have zero degrees of freedom and a CMIN of 0.000, indicating a perfect fit for the data. An extremely large p-value of.000 indicates a good fit and a considerable disagreement between the observed and predicted values in the independence model, which has 10 degrees of freedom and CMIN = 138.716. An unacceptable CMIN/DF ratio of 13.872 for the independence model indicates a poor fit, surpassing the allowed threshold of 5. After evaluating this analysis, it provides the statistical relationship between psychological biases, risk tolerance, and investment in decision making. This also shows that the default model was fit. Based on the results, it must be concluded that psychological biases and risk tolerance play an essential role in decision-making and support for alternative hypotheses (H1). Finally, we suggest the null hypothesis (H0).

Table: 11 Output Summary of RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
DM	.080	.031	.134	.137
IM	.180	.154	.207	.000

To interpret Table 11 above, we show that Root Mean Square Error of Approximation (RMSEA) values can be used to assess the importance of the correlations within the framework of the hypotheses and provide additional insights into the model fit. With an RMSEA of 0.080 for the default model, we are well inside the acceptable fit range; in general, values below 0.08 signify a good fit. Considering the bottom bound of the 90% confidence interval for RMSEA (LO 90 = 0.031, HI 90 = 0.134), which indicates a fair fit, the actual RMSEA value is probably within a respectable range. With a PCLOSE value of 0.137, we can't rule out the possibility that the model's fit is near perfect, albeit just above the acceptable range; this is because the null hypothesis, which states that RMSEA ≤ 0.05, cannot be rejected. The independence model, on the other hand, shows a poor fit with an RMSEA of 0.180. It is confirmed by the confidence interval (LO 90 =0.154, HI 90 = 0.207) that the RMSEA for this model is continuously more than the acceptable threshold of.08, indicating a good fit. The independence model's PCLOSE value of 0.000 indicates that it does not closely match the data, therefore rejecting the null hypothesis of a close fit (RMSEA ≤ 0.05). The default model provides a reasonable fit and justifies rejecting the null hypothesis (H_0) according to these results. This demonstrates that investors are susceptible to psychological biases and that risk tolerance play a substantial role in the decision-making process. Since the default model does in fact capture important and meaningful linkages, the alternative hypothesis (H_1) is further supported by the poor fit of the independence model.

Table: 12 Output Summary of Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
DM	.924	.746	.944	.804	.941
SM	1.000		1.000		1.000
IM	.000	.000	.000	.000	.000

To interpret Table 12, the various Indicators with values closer to 1.0 indicate a well-fitting model. The model's fit to the data is well supported by the NFI, IFI, and CFI values, all of which are above 0.90. Although the RFI and TLI values are lower, they are still within acceptable ranges. Notably, the TLI value is greater than 0.80, which indicates a decent model fit. The data presented here offer credence to the idea that the null hypothesis (H_0) is false and that the default model does, in fact, explain the connection between investing decision-making, risk tolerance, and psychological biases. Alternatively, the saturated model displays index-specific perfect fit values of 1.000, which is not surprising given that it is a perfectly fitted model devoid of degrees of freedom and so provides no additional information beyond what is already present in the data. With values of 0.000 across all fit indices, the independence model indicates a very good fit. This finding confirms that psychological biases and risk tolerance have a major impact on investment decision-making, and it supports rejecting the null hypothesis (H_0). It also shows that the independent model fails to account for the correlations in the data. Thus, these fit indices support the null hypothesis (H_1), adding to the growing body of evidence suggesting psychological biases and risk tolerance play a substantial role in investment decision-making.

4.6 RELIABILITY OF SCALE

A measure of the consistency of results with respect to that data collection and processing approach is known as reliability (Saunders, Lewis & Thornhill, 2007). The reliability test was characterized by the ability to reliably produce the same results when measuring the same people under the same circumstances multiple times (Hair, 2006). It is essential when surveys are constructed using a Likert scale because there are numerous aspects to evaluate. The term dependability in psychological testing has two meanings that are comparable but slightly different, according to Freeman (1965). It starts by checking for internal consistency in the outcomes. Perceived degree of accuracy is the litmus test for evaluating a given object, Second, the reliability of a measuring device is defined as the degree to which its results remain unchanged when subjected to repeated testing.

4.7 RELIABILITY OF THE CONSTRUCTS

Table: 13 Reliability Constructs

Questionnaire	CR	Cronback alpha

Psychology biases	1.862	0.893
Investor decision making	1.908	0.907
Financial risk tolerance	1.972	0.929

Table 13 consists of various constructs, psychological biases, investor decision-making, and financial risk tolerance, which were examined using reliability and internal consistency measures, such as Cronbach's Alpha and Composite Reliability (CR). A CR rating of 1.862 and a Cronbach's Alpha of 0.893 indicates psychological biases. The construct of psychological biases is highly trustworthy and internally consistent, as both values are far higher than the acceptable criterion of 0.70. The Cronbach's Alpha for investor decision-making is 0.907, and the CR value is 1.908. These numbers also show that the investor decision-making construct is reliable and consistent. The CR value (1.972) and the Cronbach's Alpha (0.929) for financial risk tolerance are significantly higher than the acceptable level, indicating that this construct is reliable and internally consistent. These strong CR and Cronbach's Alpha scores suggest that the three construct measurements are consistent and dependable. Investors' psychological biases, their risk tolerance, and their decision-making processes are all corroborated by the evidence. Because the constructs are credible, we can more confidently reject the null hypothesis (H_0), which states that investors' risk tolerance and psychological biases play a substantial role in their choice of investments. So, the results strongly support the alternative hypothesis (H_1).

V. DISCUSSION AND FINDINGS

Model fit statistical analysis for the default model shows a complex but good outcome, while a few places may use some work. With a p-value of.000, the default model's Chi-square test (CMIN) shows statistical significance, implying that the model differs substantially from a perfect match (i.e., the null hypothesis, H_0, is rejected). This lends credence to the null hypothesis (H_1), which states that investing decisions are heavily impacted by financial risk tolerance and psychological biases. With a p-value that suggests statistical significance, the model's fit is weak, as suggested by the high CMIN/DF ratio (9.870) and low fit indices (RMSEA =.149). This indicates that the model fails to adequately represent the data structure, even when proof of substantial links exists. With a Goodness-of-Fit Index (GFI) of.964 and an Adjusted Goodness-of-Fit Index (AGFI) of.865, we can conclude that the model fits the data well. Nevertheless, there appears to be a discrepancy between the predicted and observed values, as indicated by the rather large Root Mean Square Residual (RMR = 0.187). Both the RMSEA (0.149) and PCLOSE (0.000) values show that the model is not even close to fitting the data, suggesting that the fit is good. The moderate Parsimony Ratio (PRATIO = 0.400) suggests a trade-off between complexity and fit, while the low Parsimony Goodness-of-Fit Index (PGFI) of 0.257 suggests limited model simplicity. This shows that the model might use some parsimony tweaks to strike a better balance between ease of use and accuracy. In contrast to the independence model, which displays a bad fit with high RMSEA and CMIN values, the default model performs better than the alternatives. Even though it gives a perfect match, the saturated model doesn't have enough degrees of freedom to be used for meaningful comparisons. Due to its superior ability to depict the interplay between psychological biases, financial risk tolerance, and investment decision-making, the default model flaws and all is preferable to the independence model. All three constructs psychological biases (CR = 1.862, $\alpha = 0.893$), investor decision-making (CR = 1.908, $\alpha = 0.907$), and financial risk tolerance (CR = 1.972, $\alpha = 0.929$) show that they are reliable and internally consistent with high levels of reliability and Cronbach's Alpha. With such robust internal consistency, we can confidently reject the null hypothesis (H_0) and affirm the validity of the links between these constructs. The results show that psychological biases and one's level of comfort with financial risk play a major role in the investment decision-making process. Despite the fact that the default model is helpful and backs up H_1, it might be improved in a few key areas to make it even better. The model might appear to be overly difficult or improperly described due to the high RMSEA, poor parsimony indices, and high CMIN/DF ratio. Modifying the model in the future should focus on reducing residual error, improving parsimony (PNFI and PCFI), and bringing RMSEA and RMR within acceptable limits. This will strengthen the model's fit and explanatory power. Further improvement in fit might be achieved by respecifying the model to match the data more closely. Finally, the results provide substantial evidence in favor of the alternative hypothesis (H_1), which posits that investing decision-making is significantly impacted by psychological biases and financial risk tolerance. The default model performs better than the independence model and shows reliable internal consistency, especially for psychological biases, investor decision-making, and financial risk tolerance, despite some fit issues. The results indicate that, even if the model needs some work, we can reject the null hypothesis and acknowledge that psychological biases and risk tolerance are significant factors in investment decisions.

VI. CONCLUSION

The study assessing the influence of psychological biases and risk tolerance on investment decision-making using Structural Equation Modeling (SEM) yielded several key findings. For starters, it's well-established that financial risk tolerance and psychological biases like herding, overconfidence, and loss aversion greatly impact investment decisions. This lends credence to the null hypothesis (H_1), which highlights the importance of non-rational variables in determining investment decisions. Although the default model had statistical significance, certain flaws were highlighted by the model fit indices. The model did not adequately represent the data structure, as seen by the high CMIN/DF ratio (9.870) and the RMSEA (0.149), indicating the necessity for further refining to enhance its fit. High Composite Reliability (CR) values and Cronbach's Alpha scores suggest that the model's structures have great internal consistency despite these fit difficulties. By validating and confirming the conceptions of psychological biases, investor decision-making, and financial risk tolerance, these results strengthened the model's ability to capture these elements. Furthermore, the default model provided a more accurate depiction of the data than the independence model, which had bad fit indices; this provided more evidence that the proposed associations were significant. Still, the research showed that the model could use some more work. The model might use some tweaks and simplification to make it more fit and parsimonious, given the high CMIN/DF ratio and low RMSEA values. To tackle these challenges, future studies should simplify models, minimize residual errors, and investigate other variables that could interact with psychological biases, risk tolerance, and investment decisions. Ultimately, the model provides helpful information about how psychological biases and risk tolerance impact investment decisions and suggests ways to enhance them. The findings open avenues for further research on how these psychological factors influence investment behaviors and offer valuable insights for individuals making financial choices today.

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