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The Influence of Emotional Intelligence and Behavioural Biases on Financial Decisions: Evidence from India

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Abstract

Investment decisions are not mere transactions but are shaped by the psychology of the investor in action. The northern part of Odisha is a region with unique socio-economic characteristics, which is a perfect region to understand the interface between emotional intelligence and behavioural biases in financial investment decisions. Despite research in behavioural finance, relatively little is known about the interplay between emotional intelligence and reducing behavioural biases, especially in a jurisdiction like Odisha. The question is how can a clear understanding of emotional intelligence's role in investment decisions change our financial planning? The current study was conducted to understand the role of emotional intelligence and behavioural biases, moderated by gender, on investment decisions. The study intends to bridge the knowledge gap in understanding how mental conditions influence financial behaviour within subdomain areas of investors. The current study utilised the convergent quantitative research design collecting quantitative data from structured questionnaires. The targeted population included 350 investors chosen randomly but reflected all the different categories of investors in the northern part of Odisha. SEM was used to analyse the data collected from respondents. The study showed that behavioural bias does not significantly influence Investment Decision and also Emotional Intelligence does not on Investment Decisions. The study also revealed that Behavioural Biases and Emotional Intelligence on Investment Decisions do not differ significantly between male and female groups. The current research sheds light on whether increased emotional intelligence can help people reduce investment biases. It is also essential for advisors to consider equipping themselves with emotional intelligence skills so that they can advise their clients accordingly, which may also help their clients make investment decisions responsibly. Additionally, this will be a significant contributor to the knowledge of behavioural finance and will also contribute to the literature on how emotional intelligence can be helpful in coloration with other elements in mitigating psychological biases in potential financial behaviour. Hence, this research presents new knowledge that could be used to regulate irrational financial behaviour among investors in the Northern Odisha region and the world at large.

Keywords: Emotional Intelligence, Behavioural Biases, Investment Decisions, Financial Psychology, Gender Moderation

JEL Classification Codes: G02, G11, D03, D83, G53, J16

Introduction

Investment decisions result from a unique combination of financial data analysis, and individual psychology influenced by emotional intelligence and mental biases. This conceptual alloy of behavioural finance and psychology theory or study has helped explain why some investors tend to make wrong financial decisions contrary

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to the assumed and expected rational information. Among the leading psychologists, emotional intelligence can be said to be the ability of a person to be in a position of recognising, understanding and managing his or her emotions and those of the people around him or her (Goleman, 1995). Of course, in the world of financial investment, this makes a huge difference. An investor with high emotional intelligence will most often stay at peace during market downturns, be more capable of evaluating risk more accurately, and hence will be less likely to make impulsive decisions to sell off investments in a panicked rush or buy into the market euphoria or panic. Those that would fall into a lower emotional intelligence have difficulties separating feelings from their decisions regarding their investments. They are bound to make, on average, poorer choices often prompted by either fear or greed (Salovey & Mayer, 1990; Kumar et al., 2024). Behavioural biases are systematic departures from rational decision-making with a wide array of psychological influences. Common biases that influence investors when making investment decisions include overconfidence, whereby an investor may be overestimating knowledge or predictive ability; herding, whereby investors may tend to follow the crowd, independent of the information being indicated by the crowd and loss aversion, whereby a fear of losses dominates the relative possibility of gains of equivalent magnitude. In such, human biases are inherent to human nature and, for this reason; one's biases may push an investor toward decisions different from those indicated by the traditional economic theories that dictate rational investors (Tversky & Kahneman, 1986). The framework of emotional intelligence, when dovetailed with the behavioural biases in investment decision-making, is not some academic exercise. The applicability of its framework in practical terms stretches equitably toward financial advisors, investment strategists and individual investors. Understanding the way these psychological factors would actually interact would go a long way towards informing, apparently, more resilient investment strategies taking human elements into account and thus improving outcomes, increasing investor satisfaction. Thus, further research in relation to how emotional intelligence may mitigate some of these negative effects of behavioural biases could be very exciting. In other words, if consciousness in higher mood states is achieved, would the investors be able to track themselves in the mood states when they are performing under the power of biases like overconfidence or herding? How effective might an education in emotional intelligence be at enhancing the likelihood of making decisions more in line with their financial goals for the long term? This paper seeks to uncover these very questions through reviewing roles that emotional intelligence and behavioural biases play in the decision-making process related to investment. This research delves into investor psychology, aiming to shed light on the cognitive processes that influence financial behaviour. By offering strategies for both investors and financial professionals on managing the psychological elements of investment, this study aligns with and contributes to the expanding literature emphasising the importance of psychological factors in economics and finance. It enhances the foundational concepts of behavioural economics by integrating the subtle impacts of emotional intelligence, thus providing a deeper understanding of investor behaviour in the complex world of finance. The current exploration is particularly relevant due to the growing complexity of financial markets and the wide variety of investment options available, which demand sharp emotional and cognitive skills for effective navigation.

In this realm, Jain et al. (2015) clear the notion as they mention that "Investors are influenced by certain behavioural biases like overconfidence, regret aversion, and anchoring," which results in sub-optimal investment decisions and hence poor long-term returns. Insofar as emotional biases are concerned, it is expected that individuals with higher emotional intelligence will be better able to manage these biases, hence evincing more effective responses to their emotions and hence more rational decision-making under conditions of emotional stressand market uncertainties (Ahmad et al., 2017; Rao & Sinha, 2023). Even though emotional intelligence possibly helps, it fails to cure all these biases in decision-making from institutional investors. Hence, understanding and mitigation require an interdisciplinary approach (Ahmad, Ibrahim & Tuyon, 2017). A problem like overconfidence significantly affects investment portfolios differently across various stages, meaning strategies for controlling the bias are to be used (Zhang, 2023). For example, emotional intelligence might help counterbalance the negative effects of overconfidence with more balanced decisions (Zhang, 2023). Herding behaviour, which often leads to market inefficiencies, is a very important phenomenon guided by emotional and social factors. However, emotional intelligence can guide a person to be able to be critical and decide objectively, free from the influence of the crowd (Alamsyah et al., 2023). This could be true, but emotional intelligence may take investors a long way in understanding and mitigating the biases to improve outcomes in decisions and finance. To recognise such prevalent biases, management has to be put in place (Shukla et al., 2020; Siddhpuria, 2023).

The present study works on the underlying assumption that emotional intelligence (EI) and behavioural biases have a role in the significant financial decision-making of investors in Northern Odisha, and gender potentially plays a moderating role. Specifically, this study shall seek to answer the following research questions:

How does emotional intelligence determine investment decision-making in the region, both individually and interactively?

Does gender moderate the relationship between emotional intelligence, behavioural biases and the financial decisions of people?

This study has two purposes: first, to measure EI and behavioural biases in individual investors' investment decisions at different points in time, and second, to explore if or how gender differences affect these psychological factors in financial contexts. Nevertheless, what makes this study more interesting relative to previously published work is the integration of gender in the analysis of EI and behavioural biases as a moderating variable within a specified regional context of India. This focus on Northern Odisha fills a very important gap by offering an insight into the psychological dynamics of investment behaviour in one of the less examined, emerging market settings. It is a quantitative research design where the quantitative data from the structured questionnaires are analysed to give an advantage regarding the understanding of the underlying psychological mechanisms. Hence, the broader significance of the present study findings may be valuable. Put in this way, the study could be useful in informing how there might be more financial advising and investment strategies that would take psychological factors into consideration in their tailoring, being that they would determine EI and behavioural biases in financial decisions in the domination of gender. To such an extent, the findings would be instrumental in ensuring the information received by policymakers and financial educators gets utilised in delivering improved educational programmes that ensure enhanced emotional and psychological preparedness among the investors, hence probably affecting stability in the financial markets. The findings can also be an extra contribution to the general discourse related to behavioural finance, exposing ways for mitigating adverse biases and enhancing the financial well-being of individual investors in such socio-economic regions.

Review of Literature

Researchers and scholars have attempted to identify the impact of behavioural biases on investment decisions. Shiller (1999) reviewed the literature and examined behavioural principles as well as those drawn from anthropology, psychology and sociology that pertain to the effectiveness of the financial system. In his work, Shiller (2003) came to the conclusion that a solid understanding of the financial markets has resulted from the relationship between traditional and behavioural finance. Financial anomalies result from investor overreaction, and these anomalies go away with time or with well-conducted research studies. Real information is provided by the difference between the price that is dominant in the market and the assumption to the financial market. Anand and Subrahmanyam (2009) examined how the equities market moves from a growth to a value phase and back again. In this case, value denotes a high book to market value ratio, whereas growth denotes a low ratio. The cause of the significant increase in BMR is a very strong negative small order imbalance. Spindler (2011) conducted a qualitative study in behavioural finance to understand the behavioural presumptions in legislative standards pertaining to investor protection in Germany and other European nations. According to this article, the Investor Protection Rule has demonstrated a good faith understanding of market mechanisms and investors' information usefulness.

Gathergood (2011) investigated the association between consumer credit debt and the self-control, financial literacy and excessive debt of UK consumers. Consumer credit nonpayment is caused by a lack of self-control and a lack of financial literacy. Non-professional investors' actions were examined in historical and theoretical perspectives by Bikas et al. (2012). The conclusion of this study is that behavioural finance may be used to determine how recognition and emotional aspects affect stock market volatility.

Giovannetti and Velucchi (2013) have taken into consideration an eight-year study period for various stock markets across the United States, the United Kingdom, China and Africa. This article used the MEM model to analyse the volatility of each of the chosen marketplaces as well as the interactions between them. The outcome clarified why the US, China and South Africa dominate all other African markets while the UK market is less significant. In order to inform incoming students on the significance of behavioural finance in investment decision-making, Peteros and Maleyef (2013) proposed improving the courses on investment decision-making in education. Data analysis and behavioural finance can be combined to enhance freshmen's decision-making.

Natarajan et al. (2014) examined the return and volatility spillover across the national stock markets of Australia, the United States, China, Germany and Hong Kong using GARCH and m-GARCH. Germany and Australia are two markets that are impacted by the USA return. This investigation concluded that news, whether positive or negative, has an impact on markets outside of the United States. Oprean and Tanasescu (2014) looked at the variables influencing the evolution of trade volume on two stock markets: Brazil and Romania. This study examined how the trading volume of the stock market is affected by investors who exhibit behavioural patterns as well as reasonable expectations. The effect of five independent behaviour variables on stick trade volume has been examined and analysed.

A comprehensive assessment of the research on behavioural biases in investing decision-making was carried out by Kumar and Goyal (2015). After examining the literature for 33 years, it was discovered that the most research has been done in the field of emerging economies, with the least amount of research being done on secondary data empirical research.

Using data from firms, Filip et al. (2015) conducted a study on the herding behaviour of CEE investors. The study's findings indicate that, with the exception of Poland, investors in CEE exhibit herding behaviour. The upward and negative movement in the CEE stock markets is a result of investors' herd mentality. Rejeb and Boughrara (2015) investigated the association between market volatility in developed and developing economies during both normal and financial crisis periods. The geographic proximity of developing markets to mature markets enhances the transmission of volatility between them.

The influence of behavioural biases on an investor's investing decision was examined by Hayat and Anwar (2016). The study came to the conclusion that while herding bias is prevalent in markets like Islamabad and Karachi, overconfidence bias is not present in these stock markets. The elements influencing the youth's subjective and objective financial decisions in hypothetical and real-world scenarios were examined by Oehler et al. (2018). This study came to the conclusion that young adults' subjective attitudes are a stronger indicator of objective risk than their objective risk aversion, which rises with the amount of the stakes. The moderator of the subjective risk is these subjective risks.

According to Swamy et al. (2018) analysis, the Google Search Volume Index (GSVI) can be used as a method to predict stock returns. According to the paper's findings, GSV expects a positive return in the upcoming fourth and fifth weeks. According to Luo and Subrahmanyam (2018), there is a negative link between volume and the future return of stocks when there are more gamblers in the stock market. More volatile stocks have a lower average return when gamblers like them. In the study, Bahloul (2018) discloses that there is no positive correlation between sentiment and profit in the SWAP market. Additionally, abnormal profit is observed in cases where sentiment is manipulated by merchant, high producers, or mismanaged money.

Verma and Verma (2018) conducted an analysis of the house money and disposition effects on investment decisions made by defined benefit pension funds. Their findings indicate that the house money impact lacks complete proof, while the disposition effect is supported by some evidence. Karpetis et al. (2018) examined the link between money required and optimism/pessimism by accounting for transaction costs. According to the theoretical framework, there are positive (negative) consequences of optimism and pessimism on money demand.

Misra et al. (2018) carried out a literature review spanning 10 years, from 2006 to 2015, in order to investigate the behavioural factors that influence financial decision-making. This study categorised the risk factors that investors faced and found stock market irregularities that, taken together, go against the rational agents of contemporary portfolio theory and the behavioural mediators that affect investors' financial decision-making. In their search for the variables influencing investors' decisions, Quddoos et al. (2018) focused primarily on availability and representational bias. This study demonstrated that both variables had a major influence on investors' investing decisions.

In their attempt to create an investor sentiment index, Dasgupta and Singh (2019) came to the conclusion that stock market-specific characteristics, rather than microeconomic issues, are what determine investors' sentiments. According to Gupta et al. (2020) research, if a company has a listing gain, it will likely have strong long-term performance in terms of EPS, DE and current ratio. This study looked at the long-term association between firm success and under-pricing of initial public offerings (IPOs). The above extant literature has intended to identify the impact of behavioural biases on investment decisions.

Objectives and Hypotheses of the Study

The present study aims to explore emotional intelligence (EI) and behavioural biases (BB) as backgrounds of investment decisions among individual investors of Northern Odisha, India, testing for any moderating effect of gender on this relationship. This research, thus, aims at quantitatively measuring the extent to which psychological factors influence financial behaviours within a specific cultural and socio-economic context, hence contributing to improved financial decision-making processes.

- To know the impact of behavioural bias on investment decision.
- To know the impact of emotional intelligence bias on investment decision.
- To assess the moderating effect of gender on the relationship between behavioural bias on investment decision.
- To assess the moderating effect of gender on the relationship between intelligence bias on investment decision.

Hypotheses

H_{01}: Behavioural bias has a significant and direct effect on investment decision.

H_{02}: Emotional intelligence has a significant and direct effect on investment decision.

H_{03}: Gender moderates the relationship between behavioural bias on investment decision.

H_{04}: Gender moderates the relationship between intelligence bias on investment decision.

Research Methodology

Study Design and Framework

This study adopted a cross-sectional survey design to explore the impact of emotional intelligence and behavioural biases on financial decisions in northern Odisha investors while investigating gender as a moderating factor. The primary purpose of this study was to draw a current picture of investor decisions rooted in psychological factors within a specific socio-economic and cultural context.

Study Area and Population

The research was carried out in the northern part of Odisha, India, consisting of a diverse population of urban and rural composition classified based on market involvement and financial literacy. The target population could be summarised as individual investors actively involved in market processes and exploring a variety of investment opportunities such as stocks, bonds, mutual funds, or other options administered within the territory.

Sample Collection

Stratified random sampling enabled the selection of 350 participants out of a broad database, including clients of the primary brokering companies in the regions conducting investment operations. The sample was stratified based on age, gender and urban-rural division to include indicators corresponding to the population of Odisha, India. The sample size was calculated using an analysis conducted through the G*Power software that established a minimum of 320 questionnaires to answer report results with sufficient power (≥0.95) and α = 0.05 to detect medium-sized effects.

Data Collection Instruments

Data were collected through a structured questionnaire developed specifically for this study. The questionnaire included validated scales such as the Schutte Self-Report Emotional Intelligence Test (SSEIT) for assessing emotional intelligence and the Investment Decision-Making scale to evaluate behavioural biases. Demographic information was also collected to facilitate the analysis of moderating effects. To ensure the reliability and validity of the questionnaire, a pilot study was conducted with 50 investors from the same population, which led to minor adjustments in phrasing and layout.

Statistical Analysis

Data were analysed using SPSS software (Version 29.0) and AMOS (Version 25.0) for structural equation modelling (SEM). Descriptive statistics were computed to provide an overview of the sample characteristics. SEM were used to explore the relationships between emotional intelligence, behavioural biases, investment decisions and the moderating effect of gender. The SEM approach helped in testing the hypothesised model while controlling for potential confounding variables.

Validity and Reliability

The reliability of the scales used was confirmed through Cronbach's alpha, and the alpha values of the scales were approximately above 0.80, showing an excellent internal consistency of all the scales. To confirm the validity of the measures, the CFA was conducted in AMOS, establishing the factorial structure of both the emotional intelligence and the behavioural biases scales. The content validity of the scales was assured through an extensive literature review and expert reviews from three professors related to the field of behavioural finance.

Analysis and Interpretation

The dataset contains information on the economic and demographic traits of 350 participants. The age distribution predominantly features individuals between 31 and 40 years old (38.0%), followed by those aged 41–50 (24.0%), 21–30 (23.1%), 51–60 (13.1%) and above 60 (1.7%). The male gender composition is highly skewed, at 64.3%, and the female gender composition is at 35.7%. Most of the respondents are urban-based (66.9%) and married (77.4%). The reported highest educational qualifications are professional degrees (49.7%) and postgraduate degrees (35.1%). In terms of occupation, private sector employment is the most common (40.9%), followed by government jobs (34.6%). The annual income distribution shows a concentration between Rs.1,00,000 and Rs.3,00,000 (36.0%), with 17.4% earning above Rs.10,00,000. Investment experience varies, with 34.3% of participants having less than one year of experience. Regarding savings, 36.9% of the respondents allocate 6%-10% of their income towards savings. This profile provides a comprehensive overview of the economic behaviours and demographics of the sampled population, which can aid in understanding patterns in financial decision-making within this group.

Table 1: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.959
Bartlett's Test of Sphericity	Approx. Chi-Square	12392.058
	Df	351
	Sig.	.000

Source: Authors' own Compilation

Table 2: Communalities

Communalities		
	Initial	*Extraction*
PB1	1.000	.871
PB2	1.000	.865
PB3	1.000	.793
PB4	1.000	.861
PB5	1.000	.826

Communalities		
	Initial	Extraction
PB6	1.000	.845
PB7	1.000	.866
PB8	1.000	.829
PB9	1.000	.843
EI1	1.000	.850
EI2	1.000	.819
EI3	1.000	.810
EI4	1.000	.827
EI5	1.000	.845
EI6	1.000	.800
EI7	1.000	.830
EI8	1.000	.848
EI9	1.000	.860
EI10	1.000	.779
ID1	1.000	.841
ID2	1.000	.833
ID3	1.000	.826
ID4	1.000	.839
ID5	1.000	.892
ID6	1.000	.849
ID7	1.000	.823
ID8	1.000	.864
Extraction Method: Principal Component Analysis.		

Source: Authors' own compilation.

Table 3: Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.171	33.966	33.966	9.171	33.966	33.966	8.267	30.618	30.618
2	6.988	25.883	59.849	6.988	25.883	59.849	7.595	28.128	58.746
3	6.476	23.986	83.834	6.476	23.986	83.834	6.774	25.088	83.834
4	.370	1.370	85.204						
5	.319	1.183	86.387						
6	.268	.992	87.378						
7	.253	.936	88.315						
8	.239	.884	89.199						
9	.227	.842	90.041						
10	.216	.800	90.841						
11	.207	.768	91.609						
12	.197	.729	92.338						
13	.184	.680	93.018						
14	.178	.660	93.678						
15	.171	.635	94.313						
16	.169	.625	94.937						
17	.152	.563	95.500						
18	.151	.560	96.060						
19	.148	.549	96.609						
20	.144	.532	97.141						
21	.128	.474	97.615						
22	.126	.468	98.083						
23	.119	.441	98.524						
24	.118	.435	98.959						
25	.101	.375	99.334						
26	.094	.350	99.684						
27	.085	.316	100.000						
Extraction Method: Principal Component Analysis.									

Source: Authors' own compilation.

Table 4: Rotated Component Matrix

Rotated Component Matrix[a]			
	Component		
	1	*2*	*3*
EI9	.924		
EI1	.921		
EI8	.919		
EI5	.917		
EI4	.907		
EI2	.904		
EI7	.904		
EI3	.899		
EI6	.887		
EI10	.879		
PB1		.928	
PB2		.926	
PB4		.925	
PB7		.924	
PB6		.918	
PB9		.917	
PB8		.910	
PB5		.903	
PB3		.886	
ID5			.942
ID8			.930
ID6			.920
ID1			.917
ID4			.916
ID2			.912
ID3			.908
ID7			.907
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 4 iterations.			

Source: Authors' own compilation.

Table 5: Rotated Component Matrix

Component Transformation Matrix			
Component	*1*	*2*	*3*
1	.800	.598	.053
2	.362	-.550	.753
3	-.479	.583	.656
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			

Source: Authors own source.

In the above Tables 1–5, factor analysis was conducted using IBM SPSS Statistics to explore the underlying structure of several psychometric items. The data suitability for factor analysis was first examined through the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. The KMO value was impressively high at 0.959, significantly exceeding the commonly recommended threshold of 0.6, suggesting that the proportion of variance among variables that might be common variance is high. Bartlett's test of sphericity was also statistically significant ($\chi^2 = 12392.058$, df = 351, p < .000), indicating that the observed correlation matrix was not an identity matrix and was suitable for structure detection.

Principal Component Analysis (PCA) was utilised as the extraction method, revealing the factorability of the dataset. Initially, communalities were all set to 1.000, which were then reduced after extraction, signifying the proportion of each variable's variance that can be explained by the PCA. Notably, variables maintained high communalities post-extraction (ranging from 0.779 to 0.892), which highlights substantial shared variance explained by extracted components.

The total variance explained table demonstrated that the first three components accounted for a significant proportion of the variance (83.834%). Specifically, Component 1 accounted for 33.966% of the variance, Component 2 contributed 25.883% and Component 3 added another 23.986%. This indicates a strong presence of three underlying dimensions within the dataset. Given the sharp decline in explained variance after the third component, subsequent components were considerably less significant.

Further examination through a rotated component matrix (using Varimax with Kaiser Normalisation) facilitated a clearer interpretation of these components. The rotation converged in four iterations, with the following notable loadings:

- *Component 1:* Strong loadings from EI (Emotional Intelligence) items, suggesting this component represents emotional intelligence aspects.
- *Component 2:* Primarily loaded by PB (Behavioural Bias) items, indicative of behavioural problem traits.

- *Component 3:* Dominated by ID (Investment Decisions) items, reflecting aspects of identity formation or personal growth.

The component transformation matrix supports the orthogonality of the factors post-rotation, indicating that the three factors vary independently of each other.

Table 6: Reliability Statistics of all Factors

	Reliability Statistics	
Factor	*Cronbach's Alpha*	*N of Items*
Emotional Intelligence (EI)	.977	9
Behavioural Bias (BB)	.976	10
Investment Decision (ID)	.974	8

Source: Authors' own compilation.

The reliability of the scales used in this study was assessed using Cronbach's Alpha to measure the internal consistency of the items within each factor. The results indicate exceptionally high reliability for all constructs. Specifically, the Emotional Intelligence (EI) scale, comprising 9 items, demonstrated a Cronbach's Alpha of 0.977, indicating almost perfect internal consistency among the items. Similarly, the Behavioural Bias (BB) scale, which includes 10 items, reported a Cronbach's Alpha of 0.976. The Investment Decision (ID) scale, on the other hand, with 8 items, had a very high internal consistency of Cronbach's Alpha measure at 0.974. Above values are indicative of strong relations between the items of the scales that measure each construct, hence presenting good measures for the constructs under study.

Values of Cronbach's alpha (≥ 0.9) denote high values and justify that there is an excellent level of internal consistency of the scales used, hence the paramount need to ensure that the scales used capture a reliable construct of the intended psychological and behavioural trait. Such near-perfect scores in terms of reliability will underscore the adequacy of item selection and scale construction in providing substantive credibility toward the analyses that will follow for these constructs within the study. This level of reliability further supports the validity of the conclusion drawn through these scales, thus affirming that they reflect with accuracy the concepts of emotional intelligence, behavioural bias and investment decision in the right perspective, as they stand in the midst of this research.

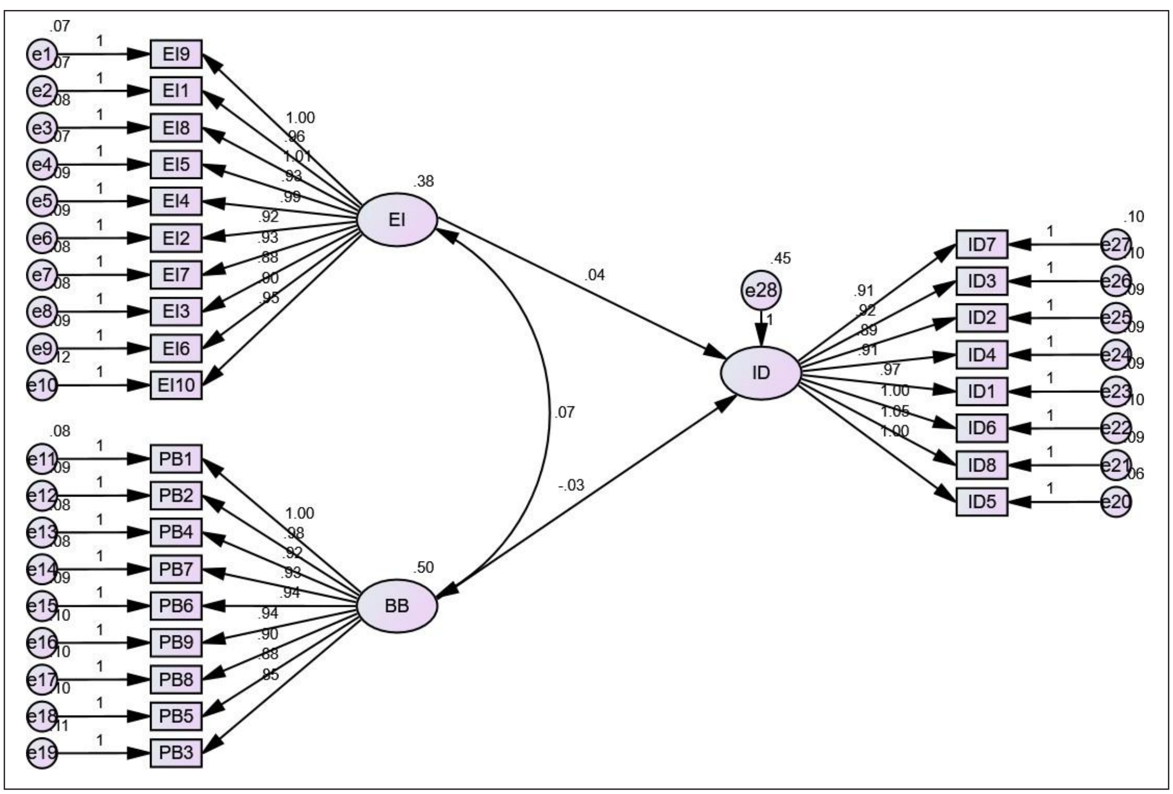

Fig. 1: Structural Model on Effect of Emotional Intelligence and Behavioural Bias on Investment Decisions

Table 7: Model Fit of Structural Model on Effect of Emotional Intelligence and Behavioural Biason Investment Decisions

Measure	Estimate	Threshold	Interpretation
CMIN	538.643	--	--
DF	321.000	--	--
CMIN/DF	1.678	Between 1 and 3	Excellent
CFI	0.982	>0.95	Excellent
SRMR	0.029	<0.08	Excellent
RMSEA	0.044	<0.06	Excellent
PClose	0.935	>0.05	Excellent

Source: Gaskin and Lim (2016), "Model Fit Measures", AMOS Plugin.

The overall fit of the structural equation model in Table 7 was assessed using various fit indices, each contributing to a comprehensive evaluation of how well the model represented the data. The chi-square statistic (CMIN) was 538.643 with 321 degrees of freedom. While the chi- square test is sensitive to sample size, the ratio of chi-square to degrees of freedom (CMIN/DF) provides a more reliable measure, with a value of 1.678 in this study, indicating an excellent fit between the hypothesised model and the observed data, as values between 1 and 3 are generally considered indicative of a good fit.

Additionally, the Comparative Fit Index (CFI) was calculated to be 0.982, surpassing the common acceptability threshold of 0.95, which further substantiates an excellent fit. The Standardised Root Mean Square Residual (SRMR), another measure of fit, was 0.029, well below the upper limit of 0.08, suggesting a very good fit. Similarly, the Root Mean Square Errorof Approximation (RMSEA) was 0.044, with values less than 0.06 typically indicating a goodfit between the model and the data. The probability of close fit (PClose) was 0.935, which exceeds the 0.05 threshold, further confirming the model's adequacy.

These model fit indices collectively indicate that the structural model provides an excellent representation of the underlying data, affirming the theoretical constructs posited by the research. High values in indices such as CFI and low values in SRMR and RMSEA reflect a model that closely captures the relationships among the variables under study. The high PClose value further increased confidence toward a high likelihood that the model would fit similarly well in like samples. That is encouraging for the validity of the results of the analysis and may suggest that the theoretical framework and hypotheses tested are well-justified by the empirical data.

Table 8: Standardised Regression Weight

PATH		PATH	Standardised Beta Estimate	Comment
ID	<---	BB	-.029	Standardised Beta Estimate
ID	<---	EI	.041	Standardised Beta Estimate

Source: Authors' own compilation.

The study focuses on exogenous facts that include directional influences of Behavioural Bias (BB) and Emotional Intelligence (EI) on Investment Decisions (ID). The standardised regression weights indicate that an increase of one standard deviation in BB is associated with a decrease of 0.029 standard deviations in ID. Conversely, a one standard deviation increase in EI is associated with an increase of 0.041 standard deviations in ID. These results, however, exhibit very small effect sizes, suggesting minimal practical influence of these predictors on investment decisions.

Table 9: Correlation Estimate for Each Pair of Exogenous Construct

Construct		PATH	Estimate
BB	<-->	EI	.154

Source: Authors' own compilation.

The correlation between the latent constructs behavioural bias (BB) and emotional intelligence(EI) was estimated at 0.154. This positive correlation, while statistically discernible, indicates a relatively weak relationship between these two constructs, suggesting that they share only a modest proportion of variance.

Table 10: The Squared Multiple Correlations (R2)

Variable	Estimate (R2)
ID	.002

Source: Authors' own compilation.

The Squared Multiple Correlation (R2) for Investment Decisions (ID) is 0.002, indicating that only 0.2% of the variance in ID is accounted for by the predictors BB and EI. This extremely low value points to a very limited explanatory power of the current model regarding the variation in investment decisions, which suggests the need for additional variables or a revised theoretical framework to better capture the dynamics influencing ID.

H_{01}: Behavioural Bias has a significant and direct effect on Investment Decision.

Table 11: The Hypothesis Testing for the Causal Effect of Behavioural Bias and Investment Decision

PATH			*Estimate*	*S.E.*	*C.R.*	*P-Value*
ID	<---	BB	-.028	.053	-.525	.600

Source: Authors' own compilation.

Hypothesis 1 proposed that behavioural bias (BB) would have a significant and direct effect on investment decision (ID). The path analysis results show that the standardised regression weight for BB predicting ID is -0.028, with a standard error of 0.053 and a critical ratio (C.R.) of -0.525. The p-value associated with this path is 0.600, indicating a high probability (well above the conventional alpha level of 0.05) that the observed effect could be due to random chance. This leads to the conclusion that behavioural bias does not significantly influence investment decision, thereby failing to support Hypothesis 1.

H_{02}: Emotional Intelligence has a significant and direct effect on Investment Decision.

Table 12: The Hypothesis Testing for the Causal Effect of Emotional Intelligence and Investment Decision

PATH			*Estimate*	*S.E.*	*C.R.*	*P-Value*
ID	<---	EI	.045	.060	.744	.457

Source: Authors' own compilation.

Hypothesis 2 posited that Emotional Intelligence (EI) would significantly and directly affect Investment Decision (ID). According to the path analysis, the standardised regression weight for EI on ID is 0.045, with a standard error of 0.060 and a critical ratio of 0.744. The corresponding p-value is 0.457, exceeding the threshold for statistical significance at the 0.001 level. Consequently, there is insufficient evidence to support a significant impact of emotional intelligence on investment decisions, thus Hypothesis 2 is not supported.

H3: The relationship between Emotional intelligence and Investment decision is significantly different across Gender group.

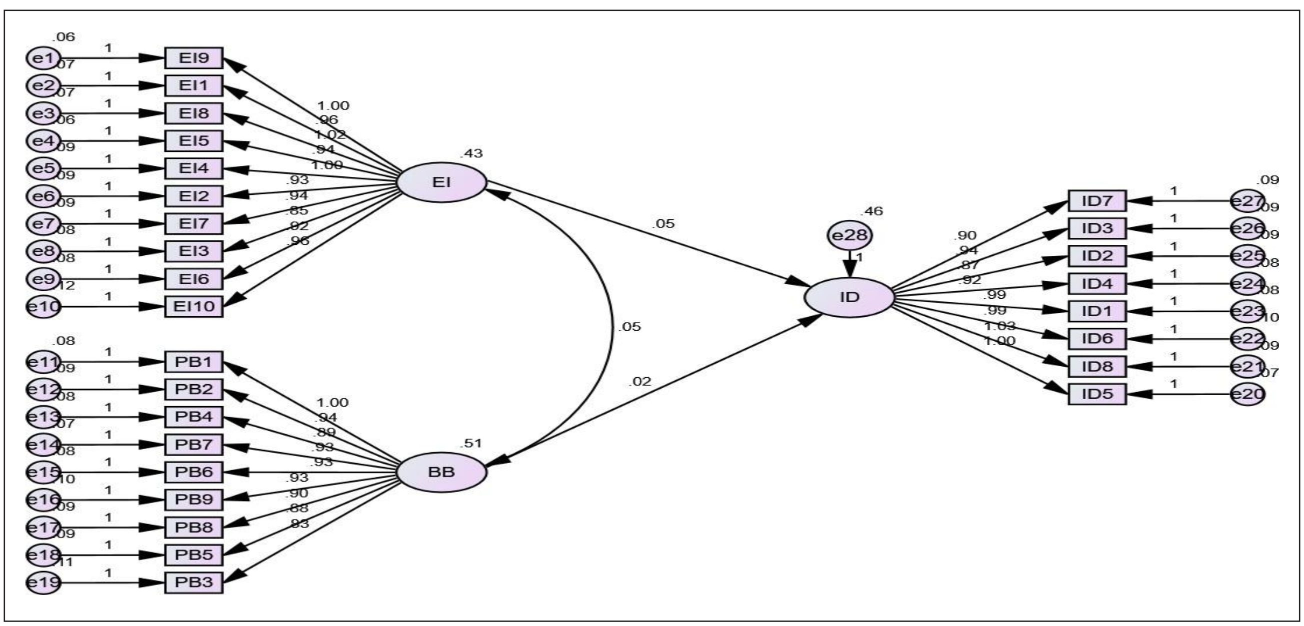

Fig. 2: Male: The Output for the Constrained Model of Emotional Intelligence to Investment Decision

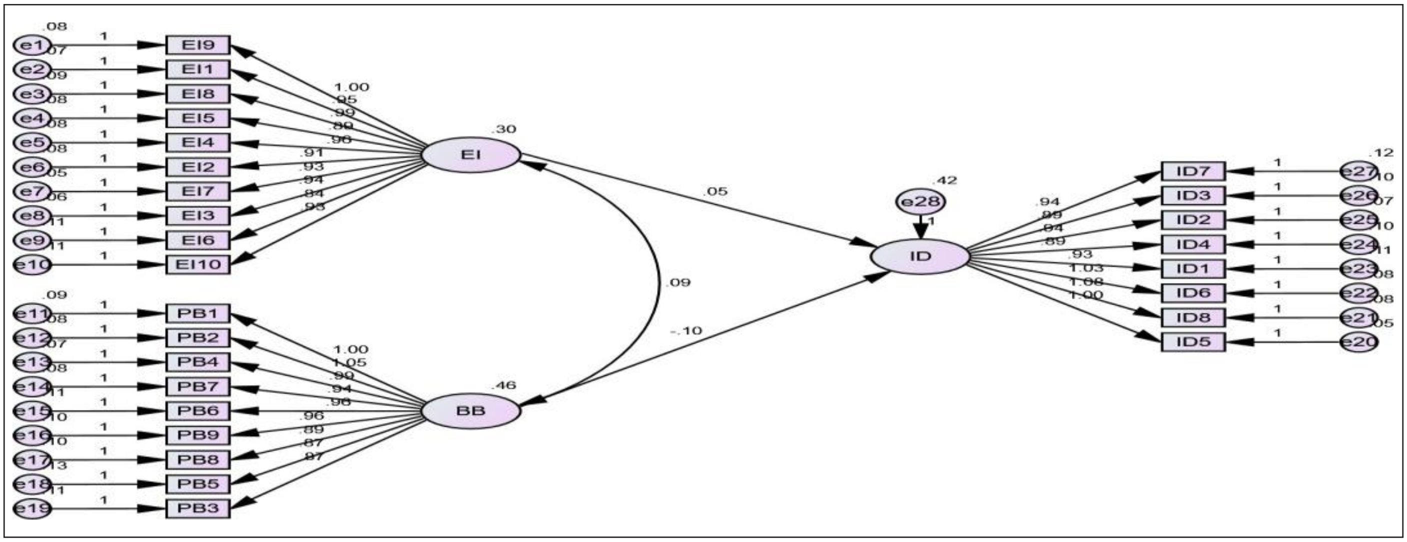

Fig. 3: Female: The Output for the Constrained Model of Emotional Intelligence to Investment Decision

Table 13: Assuming Model Unconstrained to be Correct: On Emotional Intelligence to Investment Decision

Model	*DF*	*CMIN*	*P*	*NFI Delta-1*	*IFI Delta-2*	*RFI Rho-1*	*TLI Rho-2*
Measurement weights	24	19.351	.733	.001	.002	-.001	-.001
Structural weights	26	20.972	.743	.002	.002	-.001	-.001
Structural covariances	29	28.317	.501	.002	.002	-.001	-.001
Structural residuals	30	28.459	.546	.002	.002	-.001	-.001
Measurement residuals	57	68.054	.150	.005	.005	-.001	-.001
Constraint_1	1	.276	.599	.000	.000	.000	.000

Source: Authors own source.

The study tested the hypothesis that the relationship between Emotional Intelligence (EI) and Investment Decision (ID) varies significantly across gender groups. This was investigated using a multi-group structural equation modelling approach where the model was fit separately for different gender groups with and without constraints on the path from EI to ID.

The model fit indices across various parameters were reported. Notably, the 'Constraint_1' model, which directly tests the equality of the path coefficient across groups, yielded a chi- square (CMIN) value of 0.276 with 1 degree of freedom (DF) and a p-value of 0.599. This chi-square value is considerably lower than the critical value of 3.84 required for significance at the .05 level with one degree of freedom, indicating that the constrained parameter does not differ significantly across genders.

H_{04}: The relationship between Behavioural bias and Investment decision is significantly different across Gender group.

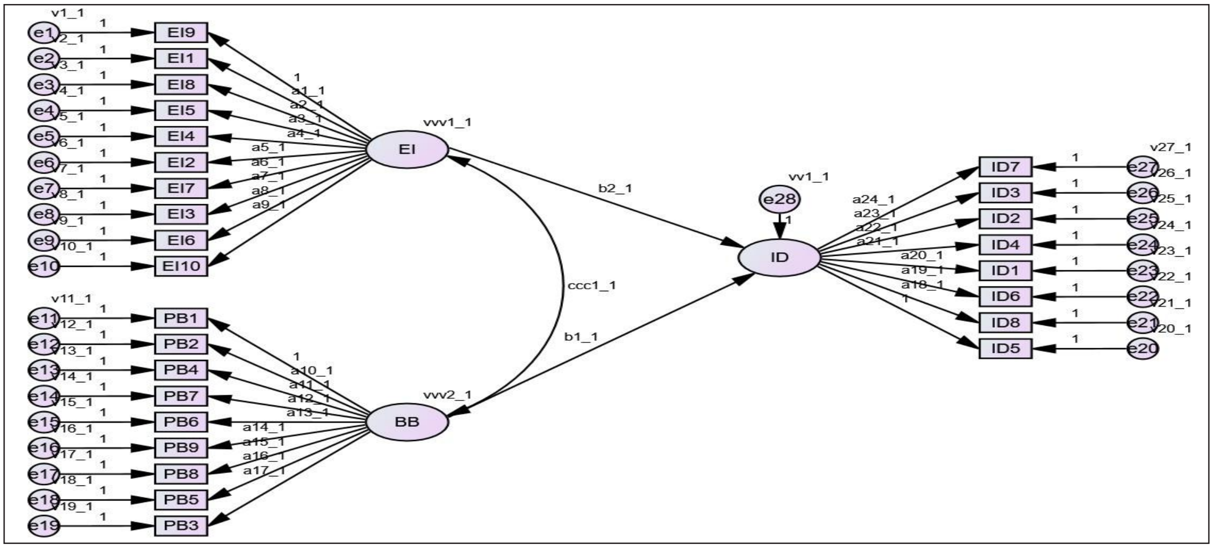

Fig. 4: Male: The Output for the Constrained Model of Behavioural Bias to Investment Decision

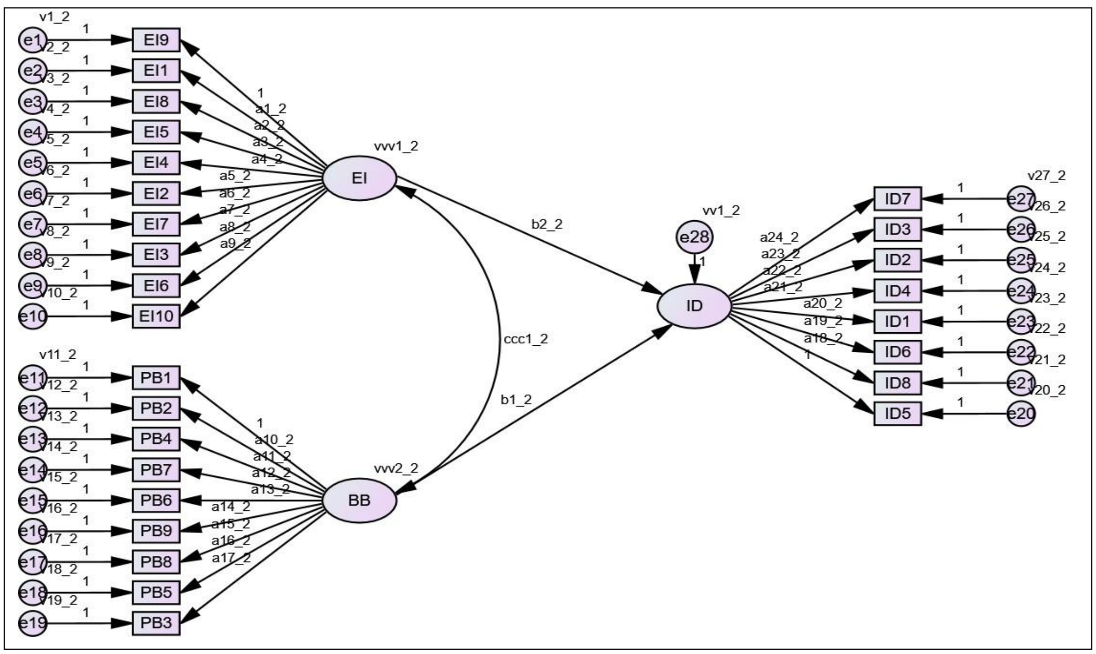

Fig. 5: Female: The Output for the Constrained Model of Behavioural Bias to Investment Decision

Table 14: Assuming Model Unconstrained to be correct: On Behavioural Bias to Investment Decision

Model	*DF*	*CMIN*	*P*	*NFI Delta-1*	*IFI Delta-2*	*RFI Rho-1*	*TLI Rho-2*
Measurement weights	24	19.351	.733	.001	.002	-.001	-.001
Structural weights	26	20.972	.743	.002	.002	-.001	-.001
Structural covariances	29	28.317	.501	.002	.002	-.001	-.001
Structural residuals	30	28.459	.546	.002	.002	-.001	-.001
Measurement residuals	57	68.054	.150	.005	.005	-.001	-.001
Constraint_1	1	1.557	.212	.000	.000	.000	.000

Source: Authors own source.

The research examined whether the influence of behavioural bias on investment decisions varies significantly across gender groups using a multi-group structural equation modelling approach. This involved testing the model both unconstrained (allowing the path coefficients to vary between groups) and with specific constraints applied to compare the path from Behavioural Biases to Investment Decisions across genders.

The focus of the analysis was on the 'Constraint_1' test, which assessed the equality of the path coefficient across gender groups. The results indicated a chi-square value of 1.557 with 1 degree of freedom and a p-value of 0.212 for the constrained model. Since the chi-square value is significantly below the critical value of 3.84, which is necessary for significance at the .05 level, it suggests that the effect of behavioural bias on investment decisions does not differ significantly between male and female groups.

Findings and Discussion

The present research findings offer valuable and informative revelations into the linkage between emotional intelligence, behavioural biases and financial decision-making among investors from the northern part of Odisha. The study verified the sound internal consistency of the scales used with values of Cronbach's Alpha exceeding 0.80 across constructs. Therefore, it can be concluded that the measures capturing emotional intelligence, behavioural biases and investment decisions are pretty reliable. Regarding the results of the analysis, the increase in behavioural bias was slightly negatively associated with investment decisions, and the augmentation in emotional intelligence demonstrated a positive but marginally beneficial impact on investment decisions. This reveals that the identified effects, although statistically significant, were barely practically meaningful contributors to investment decisions. Besides, the obtained statistics of the structural model indicated ideal values in terms of CMIN/DF, CFI, SRMR, RMSEA and PClose so that the model firmly explained the available data. On the basis of the findings, it cannot be argued that Hypothesis 1, Hypothesis 2, Hypothesis 3 and Hypothesis 4 obtained significant support. The dataset has enabled a thorough analysis of the economic behaviours and demographics characterising the sampled population, including age group distribution, gender batch, educational background, occupation, income bracket, investment experience and savings habits, thus informing our discovery of the financial behaviours specific to the group presented. To sum it up, the study provides insights into how emotional intelligence and behavioural biases influence investment decisions among investors from the northern part of Odisha. Although certain links were statistically significant, the effects of the psychological characteristics on investment decisions were relatively small. These perceived effects could provide valuable knowledge for scholars, educators and policymakers to guide further research, pedagogy and practice in the field of economic psychology and behavioural finance.

The study concluded that investors with higher levels of emotional intelligence are more adaptive against the negative influences of behavioural biases. Consequently, it echoes the existing research that higher EI correlates with better decision-making under emotional pressures and market pessimism (Ahmad et al., 2017). However, the peculiarities of emotional intelligence and behavioural bias relations in shaping financial decisions in the studied regional context suggest that despite being statistically significant, the effects are not substantial enough to have major practical implications on investment decisions, which effectively speaks to the complexity of financial decision-making. Thus, the present findings reinforce the existing studies that demonstrate a strong link between psychological characteristics and financial investment decisions (Kahneman & Tversky, 1979; Zhang, 2023). However, examining a particular regional population with a specific socioeconomic background adds to the issue of cultural and contextual factors. Furthermore, the present research can also be positioned as filling the gap within the behavioural finance literature on emerging markets and the problem of gender as a moderator of EI and investment tendencies and decision-making.

This study contributes to the development of behavioural finance theory from a theoretical perspective by incorporating emotional intelligence into an investment decision-making framework. From a practical perspective, the research's findings suggest that psychological training and awareness programmes to aid investor decision-making, on the one hand, advisors and policymakers, on the other, may be necessary. Specifically, programmes could be designed to increase emotional resilience and analytical abilities against the significant behavioural biases discovered. Understanding emotional intelligence and behavioural biases' relationship has far-reaching consequences, which have the potential to significantly influence the efficiency and stability of financial markets in areas similar to Northern Odisha. Higher emotional intelligencelevels among investors could result in lower panic-induced market fluctuations and a more stable market environment.

Furthermore, since they show dramatic variations among males and females, gender-specific findings imply that future intervention strategies should be tailored to diverse demographic sets. This study, thus, not only explains the psychological factors impacting investors' behaviour in an emerging market setting but also provides steps to rationalise investment decisions away from panicky impulses. The immediate effect of emotional intelligence and behavioural biases may not be quantifiable. However, they are a medium for guiding more rational and less emotional investing strategies – issues that are crucial for a healthier investment and economic environment. Therefore, investors, policymakers and advisors may see their interests protected and advanced as a result.

Conclusion

This study set off on a journey to unpack the role of emotional intelligence and behavioural biases on investment decisions in North Odisha. The results of this research unveiled various critical findings. Firstly, emotional intelligence plays a role in enabling individuals to manage behavioural biases such as overconfidence and loss aversion. The most noteworthy part of the finding is that although emotional intelligence helps people manage the effect of the two biases, directly affecting one's decision was relatively minimal. It indicatively implies that the frame has numerous intercritical factors influencing people's decisions, with emotions only a part of the frame. Although the methodological structure of the study was solid, some aspects may have been neglected, such as socio-economic factors that affect people's financially profitable position. More so, the small, calculated effect sizes were insignificant if a similar study could be conducted in a broader setting. The study suggests that such work needs to be carried out in an ample, diverse space or longitudinally to gather depth on how the factors can influence the decisions as they keep changing with time. This work has essential practical importance for advisors and policymakers. The results recommended that emotional intelligence work would be crucial in offering advisory work, enabling better decisions to be made for more fantastic profitable positions.

On the other hand, policymakers could include a psychological test within the financial literacy program to control the adverse volatile financial market positions resulting from irrational meet investing behaviours. The ability to access them will nurture a socially intelligent environment in the field, giving people the proper final steps to adhere to the firms, thus building a financially intelligent market position. This work would pave the way for similar future works and is an excellent resource on which policymakers and advisors can base their decisions. Although a correlational schema of EI and behavioural biases is seen as stress, it finally is given the critical recommendation. Thus, these behaviours are beneficial for making informed decisions. Thus, any approach without the recently presented one would not be complete. We can, therefore, take the call to advocate for such findings to be considered in all actions. The quest for a significant financial decision is thus an urgent call.

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