Analyzing the Robust Factors of Overconfidence Bias and its Impact: An Interpretive Structural Modeling Approach

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Abstract

People have a tendency to have too much reliance on the accuracy of their own judgments. This inclination boosts up the confidence limit of an individual, as people have the propensity to compare quantity with quality. Overconfidence is one of the prominent behavioral traits, which persuade an individual to make poor investment decisions without doing an impartial analysis of the available options. The distortion in the investment decision-making process is led by overconfident behavior which itself is adversely affected by a few of the factors. The objective of this paper was to explore and develop the relationships among the reviewed variables by keeping at the center the psychology of stock market investors. The interpretive structural modeling (ISM) methodology was used for identifying the prominent factors in a sequential manner. This provided a hierarchical structure apprenticing with planning, execution, categorizing, and conclusion, by way of providing output for the whole process. The factors were categorized as drivers, enablers, and dependent variables in the hierarchy of the ISM model. This model provided a framework for investors to spot out the robust factors of overconfidence in an orderly manner in the stock market, which distorts the investment decision making process.

Keywords: behavioral traits, hierarchical structure (drivers, enablers, and dependent variables), interpretive structural modeling

JEL Classification: C6, G00, G02

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Decision making is a complex process which requires understanding of varied individual specific factors, market happenings, and technical fronts. The individual specific factors or demographic factors such as age, gender, income, occupation, education, and so forth along with financial models and happenings in the surroundings affect the decisions of an investor. Chandra (2008) stated that investment decisions should never be deprived of financial models as they are based on expected risk and return continuum. Situational factors are prominent factors which cannot be explained by the way of financial modeling, and thus, paved way for an emerging field, that is, 'behavioral finance.'

The incorporation of psychology to finance attempts to understand how investors, in general, forget the fundamentals and make decisions on the basis of their emotions and cognitions. These cognitive and emotional biases distort the decision-making process of the investors. Once the investors are able to identify and sway away these psychological errors, they will be able to develop their optimum portfolio and achieve their investment goals.

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The father of efficient markets, Eugene Fama introduced the concept of 'efficient market hypothesis' (EMH) in 1970, which is entitled with the connotation that prices of a security reflect all the available information. Eugene Fama, the Nobel Memorial Prize Winner of 2013 in Economic Sciences familiarized the world with three phases of markets, which are discussed below :

(1) Weak Form : It asserts that future prices cannot be predicted by analyzing the historical trends, thus technical analysis is of no use.

(2) Semi-Strong Form: It postulates that security's prices reflect all the publicly available information, thus fundamental analysis is of no use as abnormal returns cannot be earned by trading on that information.

(3) Strong Form: It implies that share prices reflect both publicly available information as well as insider information, and hence, no investor can earn abnormal returns.

Traditional theories of finance assume an investor to be rational, but many researchers and scholars criticize the hypotheses of efficient markets with the notion that if investors would have been rational enough, every investor must have earned equivocally, but it does not happen. The field of behavioral finance assumes the investor to be quasi-rational or irrational because the investment decision making process is driven by human errors in reasoning and information processing. This gives rise to varied cognitive and emotional biases which distort the whole process of achieving goals of investments. One of the prominent cognitive biases is 'overconfidence'. Kahneman and Tversky (1996) defined confidence as a belief which one thinks that 'it will happen' ; whereas, according to Gigerenzer, Hoffrage, and Kleinbölting (1991), overconfidence is a condition where confidence judgment goes beyond the frequency of correct answers.

Overconfidence Bias

Overconfidence has been evidenced as an active field of research from the past so many years. It can be described as a bad timed belief imbibed with false reasoning, judgment, and beyond an individual's cognitive abilities which mismatch with reality. According to Glaser and Weber (2007), overconfidence is a pervasive phenomenon and has a very brutal impact on investment decisions. They opened the layer of overconfidence associating it with miscalibration and better than average effect. The manifestation in quantifying things efficiently and having a sense of analyzing and predicting future outcomes better than others surpasses the notion of becoming overconfident in a respective domain.

Varied research shows that investors exaggerate their investing ability, which is backed by the following dimensions:

(i) Prediction Overconfidence : Investors set too narrow range of their predictions. Too much emphasis on potential investment or desirable outcome is followed by forecasting of future possible returns. This has next to impossible connection with their objective likelihood (Giardini, Coricelli, Joffily, & Sirigu, 2008).

(ii) Certainty Overconfidence : Investors often tend to excessively rely on their judgments, which they assume to be certain in the times to come. An overconfident investor becomes blind to negative information. They are always in a rush in the search of the 'next hot stock'. Literature also supports that overconfident investors hold undiversified portfolio, which stimulates the error of making right investment decisions. In the literature frameworks, overconfidence has been defined by varied authors, scholars, and researchers. The overconfidence trait is explored in varied research work. The Table 1 gives an insight to understand the term given by various authors and scholars.

Table 1. Research on Overconfidence by Authors and Scholars

S.No.	Authors	Overconfidence in Words
1	Block & Harper (1991)	Cognitive conceit
2	Koriat, Lichtenstein, & Fischhoff (1980)	Calibration of Probabilities
3	Chen, Kim, Nofsinger, & Rui (2007)	One's tendency to overestimate ability
4	Moore & Healy (2008)	Overestimation of one's performance, level of control, and chance of success
5	Skala (2008)	One of the forms of miscalibration
6	Oskamp (1965)	Excess of confidence over accuracy
7	Kahneman & Lovallo (1993)	Planning Fallacy
8	Pompian (2011)	Unwarranted faith in one's intuitive reasoning, judgment, and cognitive abilities
9	Nofsinger (2011)	A degree of overoptimism and illusion of control
10	Barber & Odean (2001)	Incorrect judgment about knowledge, ability, and future prospects

Review of Related Literature and Identification of Variables Affecting Overconfidence

Overconfidence is a robust phenomenon which affects the decisions to a great extent. In the recent past, the core of the global financial crisis 2008 was backed with overoptimism, overconfidence, and categorization, which led to financial instability.

Glaser and Weber (2007) identified a number of factors for measuring the degree of overconfidence such as : elicitation methods, hard and easy effect, gender, culture, available amount of information, monetary incentives, and effect of expertise on judgment. Pulford (1996), in his doctoral thesis, explored the factors which influence the degree of confidence, such as : task difficulty, information, practice and expertise, base rate, locus of uncertainty, individual differences, mood/depression, and gender.

Keysey and Watson (1989) looked at four factors which influenced the accuracy-confidence relationship, that is, feedback, complexity of a task, motivational level, and skill of the subject. The empirical findings of Park, Konana, Gu, Kumar, and Raghunathan (2010) explored that strong beliefs of an investor give support to confirmation bias and experience negative performance. This confirmation bias changes the way for evaluating the scenario and interpreting the information, moreover, the whole process of information search.

Glaser and Weber (2007) correlated investment measures of investors with better than average effect, miscalibration, unrealistic optimism, and illusion of control. The study concluded that overestimation of precision leads to overconfidence. Other than that, calibration must be treated with much more vigilance.

The summarized form of identified variables (referred to as the Elements) affecting overconfidence in trading behavior are given below along with their impact on an individual's portfolio:

(1) Miscalibration: It simply means incorrect calibration. Investors initially set too narrow limit for their predictions, which in a pseudo manner, makes them feel that their precision of analysis is in a right direction. The too narrow range of boundary limits results in frequency of trading. Seppala (2009) implied that in the first round of making investments, investors were found to be overconfident as they set a too narrow limit, which is too far from the confidence boundary. It was also evidenced that investors underestimate volatility and do not take lessons from volatility. Due to this, in the second round of investment, they believe their past decisions have been successful, and it leads to overconfidence. Investors are ordinarily in a tandem to be optimistic for expected returns, it gives rise to overestimation. Moreover, people in general believe that they can control the events as they wish and desire. Nofsinger (2011) framed the drivers for the illusion of control such as task familiarity, choice, outcome sequence, information, and active involvement. This behavioral trait of investors leads them to feel to have the outcomes they wanted to have in their desired manner.

(2) Rising Trends in the Markets : If rising trends occur more often, investors become optimistic and trade heavily ; this gives seed to overconfident behavior. Inaishi, Toya, Zhai, and Kita (2010) applied the multi agent simulation and explored that rising trends in stock markets lead to overconfidence among investors. This phenomenon is also supported by overoptimism and illusion of control. The backing of overoptimism does not tender investors to learn from their past mistakes and the illusion of having control in their hands for the events to come surpasses the notion of miscalibration.

(3) Volume of Trade: The prominent factor of volume of trading is also linked with overconfidence. The overconfident investors generally trade frequently and trade in volume. Glaser and Weber (2007) found that those who think they are better than others, they trade in large volumes.

(4) Frequency of Trading : Investors who feel more comfortable with the thick and thins of the stock market generally trade frequently and in volume. Trinugroho and Sembel (2011) found that overconfidence is directly related to frequency of trading along with volume of trading. It was also evidenced in their study that if bad news is being floated in the market, investors with low confidence tended to panic ; whereas, overconfident investors were indifferent during the phase of pre and post bad news.

(5) Illusion of Knowledge: Montier (2007) warranted that the propensity for investors to believe that their precision of accuracy gets doubled with the level of information - this inclination is termed as illusion of knowledge, which is one of the strongest pillars for the high degree of confidence.

(6) Price Distortion: The mispricing of security and price deviation from fundamentals also strike the level of confidence. The deviation in prices of security smashes the dynamics of overestimation. The literature supports the views that the severity sometimes results in crashes and bubbles (Yeh & Yang, 2011).

(7) Undiversified Portfolio: Theories of finance evidenced that the diversification of portfolio reduces risk. Odean (1998) found that overconfident investors frequently trade and hold an undiversified portfolio because they overestimate their skill of precision of interpreting the information. Thus, overconfidence results in undiversification of portfolio.

(8) Investment Experience : Deaves, Luders, and Schroder (2005) opined that overconfidence is nothing but a situation where knowledge perception goes beyond reality. They emphasized that past successful triggers lead to self-attribution, which ultimately gives a green nod to overconfident behavior. In the series, the authors also explored that years of market trading experience and market wide returns also give input for accelerating this prominent bias.

(9) Better than Average Effect : People in general tender themselves with better skills than others and they always exaggerate their views for self. They consider themselves better informed, better skilled, and more experienced and knowledgeable than others, which sways them to make poor investment decisions. Taylor and Brown (1988) explored that people overrate themselves on the grounds of skills and personality attributes.

(10) Underestimation of Risk : Odean (1998) also uncovered that overconfidence also results in underestimation of risk as overconfident investors boast of their future predictions. This has to be reduced by having a high degree of skill and knowledge and interpreting the information in the right direction.

(11) Expectation of Beating the Market : The power of overconfident investors for predicting the market and exaggerated trading ability make investors think that they can beat the market (Merkle, 2013). The past successful hits also contribute to the path of beating the market.

Table 2. Few Applications of ISM in Varied Industries

S.No.	Authors	Area of Study
1	Agarwal, Shankar, & Tiwari (2007)	Modeling Agility of Supply Chain
2	Sahney (2008)	Critical Success Factors of Online Retail
3	Luthra, Kumar, Kumar, & Haleem (2011)	Customer Involvement in Greening the Supply Chain
4.	Sohani & Sohani (2012)	Quality Framework in Higher Education
5.	Gorvett & Liu (2006)	Identify & Quantify Interactive Risks

(12) Frequency of Information: Investment in information also hits the level of overconfidence. The overconfident investors spend more in search of information, which persuades them for frequent trading, and this results in lower returns in a portfolio. Guiso and Jappelli (2005) proposed a contrary view that the amount of information leads to good analysis, which leads to efficient portfolio performance. Moreover, the access of the private or confidential source of information also advances the level of confidence.

(13) Reduction in Turnover/Earnings : The scholarly article of Barber and Odean (2001) on gender based study evidenced that the tendency of trading more frequently results in underestimation of risk and undiversified portfolio, which ultimately results in reduction in turnover or earnings.

(14) Poor Portfolio Performance : Overconfident investors trade too frequently and volume of trading is also high (Pompian, 2011). It results in lesser average returns. They underrate the downside of ultimate risks, and the undiversification of portfolio generally ends up with poor portfolio performance.

The 14 elements discussed above give a fleeting look at the impact of overconfidence on the performance of a portfolio. Modeling of these elements helps in the direction of looking at the severity of not managing and controlling the behavioral aspect of overconfident behavior.

Objective of the Study

The objective of the paper is to discuss the complexities of the elements for understanding the overconfidence bias and its impact. This model will discuss and pave the way for a framework for investors to spot out the robust factors of overconfidence in an orderly manner in the stock market which distorts the investment decision-making process.

Methodology

Interpretive structural modeling approach (ISM) was developed by John N. Warfield in 1973. ISM provides a basis for understanding and solving complex issues and provides the solution for the same. The process is interpretive in the sense that on the basis of expert discussions and opinions, the relationship between the variables is identified, which serves as a foundation stone for solving complex issues.

The available literature does not provide a glance at the ISM approach being used for behavioral finance studies. The Table 2 highlights some of the prominent research work conducted using ISM. The present paper is an attempt to explore the uncovered area for finding out the interrelationships of the elements with one another and looking at the impact on portfolio performance.

Table 3. Self Structured Interaction Matrix (14 Elements)

Elements	14	13	12	11	10	9	8	7	6	5	4	3	2
1	X	V	O	A	V	X	O	V	X	A	X	V	V
2	X	V	A	A	V	V	A	V	V	V	V	V	1
3	V	V	A	A	V	A	A	X	V	X	X	1	
4	V	V	A	A	V	X	O	V	X	A	1		
5	V	V	A	A	V	O	O	O	V	1			
6	V	V	A	A	V	A	A	X	1				
7	V	V	A	A	V	O	A	1					
8	V	V	A	A	V	V	1						
9	V	V	A	A	V	1							
10	V	V	A	A	1								
11	V	V	V	1									
12	V	V	1										
13	V	1											
14	1												

➪ **Development of the ISM Model :** The varied steps involved in the ISM technique are:

(1) Identification of elements which affect the overconfidence bias through literature review.

(2) Establishing an appropriate relationship amongst the elements pair wise with the help of expert opinion.

(3) Developing a structural self interaction matrix (SSIM) which is known as VAXO.

(4) Creating a reachability matrix through SSIM and checking the existence of transitivity. Transitivity sways if *A* is having a relation with *B* and *B* is having a relationship with *C*, then *A* also relates to *C*.

(5) Partitioning the final reachability matrix into the derived levels.

(6) Developing the diagraph on the basis of a final reachability matrix by eliminating the transitivity.

(7) Converting the directed graph into an ISM based model.

(8) Revising the model if there is any conceptual inconsistency and modifying it accordingly.

➪ **Developing a Contextual Relationship Between the Variables :** Through the literature review, the variables were identified which boost overconfidence amongst investors. Next, contextual relationships between the variables were explored. The association between two variables *(i, j)* were analyzed for making the structural self-interaction matrix. The following is the blueprint for denoting the relationship between (*i* and *j*). The four prototypes which are available for marking the relationship between the variables are as follows :

V **:** Variable *i* will assist to achieve variable *j* ;
A **:** Variable *j* will assist to achieve variable *i* ;
X **:** Variable *i* and *j* will assist to achieve each other ;
O **:** Variable *i* and *j* are unrelated.

➪ **Structural Self- Interaction Matrix (SSIM) :** The SSIM (Table 3) was developed with a mode of discussion with a panel of experts. The relation and association between the variables were analyzed on the basis of their responses.

Table 4. Initial Reachability Matrix

Elements	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1	1	1	1	0	1	1	0	1	1	0	0	1	1
2	0	1	1	1	1	1	1	0	1	1	0	0	1	1
3	0	0	1	1	1	1	1	0	0	1	0	0	1	1
4	1	0	1	1	0	1	1	0	1	1	0	0	1	1
5	1	0	1	1	1	1	0	0	0	1	0	0	1	1
6	1	0	0	1	0	1	1	0	0	1	0	0	1	1
7	0	0	1	0	0	1	1	0	0	1	0	0	1	1
8	0	1	1	0	0	1	1	1	1	1	0	0	1	1
9	1	0	1	1	0	1	0	0	1	1	0	0	1	1
10	0	0	0	0	0	0	0	0	0	1	0	0	1	1
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	0	1	1	1	1	1	1	1	1	1	0	1	1	1
13	0	0	0	0	0	0	0	0	0	0	0	0	1	1
14	1	1	0	0	0	0	0	0	0	0	0	0	1	1

Table 5. Final Reachability Matrix

Elements	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1	1	1	1	1	1	1	0	1	1	0	0	1	1
2	***1***	1	1	1	1	1	1	0	1	1	0	0	1	1
3	***1***	0	1	1	1	1	1	0	***1***	1	0	0	0	1
4	1	0	1	1	0	1	1	1	1	1	0	0	1	1
5	1	0	1	1	1	1	0	0	0	1	0	0	1	1
6	1	0	0	1	0	1	1	0	0	1	0	0	1	1
7	***1***	0	1	0	0	1	1	0	0	1	0	0	1	1
8	0	1	1	0	0	1	1	1	1	1	0	0	1	1
9	1	0	1	1	0	1	0	0	1	1	0	0	1	1
10	0	0	0	0	0	0	0	0	0	1	0	0	1	1
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	0	1	1	1	1	1	1	1	1	1	0	1	1	1
13	0	0	1	0	0	0	0	0	0	0	0	0	1	1
14	1	1	0	0	0	0	0	0	0	0	0	0	1	1

➭ **Development of the Initial Reachability Matrix :** The SSIM was then converted into a binary matrix, which is also known as the reachability matrix. The application of *VAXO* in each row and column as per the case by putting 1 and 0 was followed. The situation of the matrix was developed as given below :

(1) If the [*i, j*] entry in the SSIM is *V*, the [*i, j*] entry in the reachability matrix becomes 1, and the [*j, i*] entry becomes 0.

(2) If the [*i, j*] entry in the SSIM is *A*, the [*i, j*] entry in the reachability matrix becomes 0, and the [*j, i*] entry becomes 1.

Table 6. Partitioning the Reachability Matrix

Elements	Reachability Set	Antecedent Set	Intersection	Level
13	13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14	13,14	I
14	1,2,13,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14	1,2,13,14	I
10	10	1,2,3,4,5,6,7,8,9,10,11,12	10	II
2	1,2,3,4,5,6,7,9	1,2,3,4,5,6,7,9,11	1,2,3,4,5,6,7,9	III
6	1.4.6.7	1,2,3,4,5,6,7,8,9,11,12	1,4,6,7	III
7	1,3,6,7	1,2,3,4,6,7,8,11,12	1,3,6,7	III
1	1,3,4,5,9	1,3,4,5,9,11	1,3,4,5,9	IV
3	1,3,4,5,9	1,3,4,5,8,9,11,12	1,3,4,5,9	IV
9	1,3,4,9	1,3,4,8,9,11,12	1,3,4,9	IV
8	8	4,8,11,12	8	V
4	4	4,5,11,12	4	VI
5	5	5,11,12	5	VII
12	12	11,12	12	VIII
11	11	11	11	IX

(3) If the [*i, j*] entry in the SSIM is *X*, the [*i, j*] entry in the reachability matrix becomes 1, and the [*j, i*] entry also becomes 1.

(4) If the [*i, j*] entry in the SSIM is *O*, the [*i, j*] entry in the reachability matrix becomes 0, and the [*j,i*] entry also becomes 0.

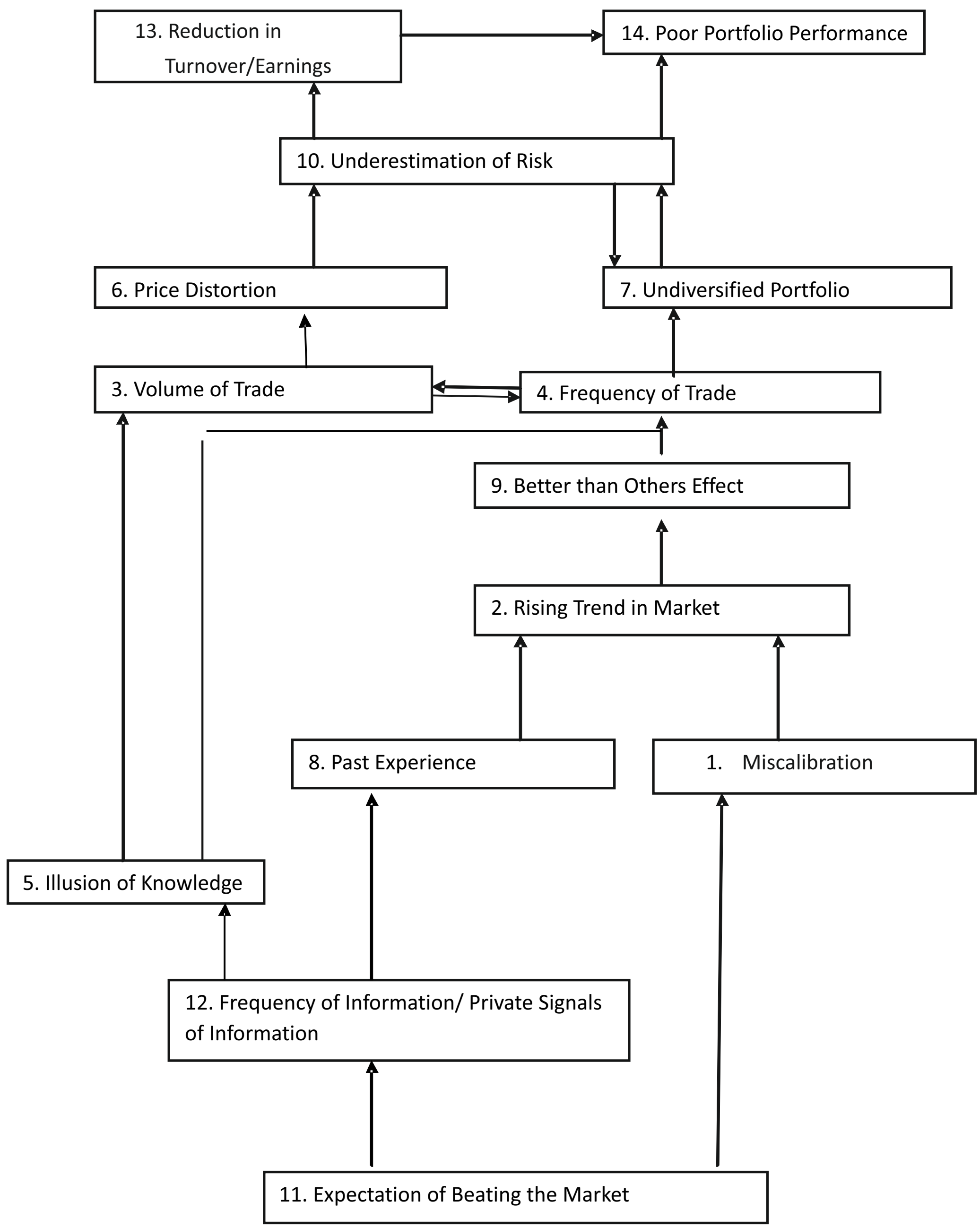
The above stated rules were applied to construct the Table 4 for the initial reachability matrix.

➯ **Final Reachability Matrix :** Supplement to the above step, 1* entries were taken to incorporate transitivity for seeking the indirect relationship amongst the reviewed variables. The final reachability matrix is depicted in Table 5 after considering transitivity.

➯ **Partitioning the Reachability Matrix :** The matrix was further segregated by evaluating the reachability and antecedent sets for each of the variables identified. The reachability set includes the element itself and the rest of the elements which it may help to achieve. On the other hand, the antecedent set was constructed by including the element itself and the variable which may help in achieving it. The next in the series is to derive the intersection sets out of the reachability and antecedent sets. The variables for which reachability and intersection sets are equivalent, they are placed at the top of the ISM hierarchy. From this point, the top placed elements are then separated out from the rest of the elements both in the row and the column direction. This process goes on till the final iteration is being prepared, considering all the reviewed variables. The whole process is completed in nine iterations, which is depicted in the Table 6.

It is observed that the Expectation of beating the market (11), Frequency of information (12), Illusion of knowledge (5), Rising trends in the markets (2), and Investment experience (8) play a significant driving role for accentuating the overconfident behavior. These drivers give a nod to Miscalibration (1) and Better than others effect (9), which results in Volume of trading (3) and Frequent trading (4). The trading practices distort the prices (6), which ultimately result in an undiversified portfolio (7), Investors underestimate the downside risk (10), Reduces the turnover/earnings (13), and ultimately, impact can be seen on investors' portfolio performance (14).

Figure 1. ISM Based Model



➾ **Development of the Diagraph :** The diagraph is converted into an ISM model by replacing the nodes of the factors with statements and this is depicted in the Figure 1.

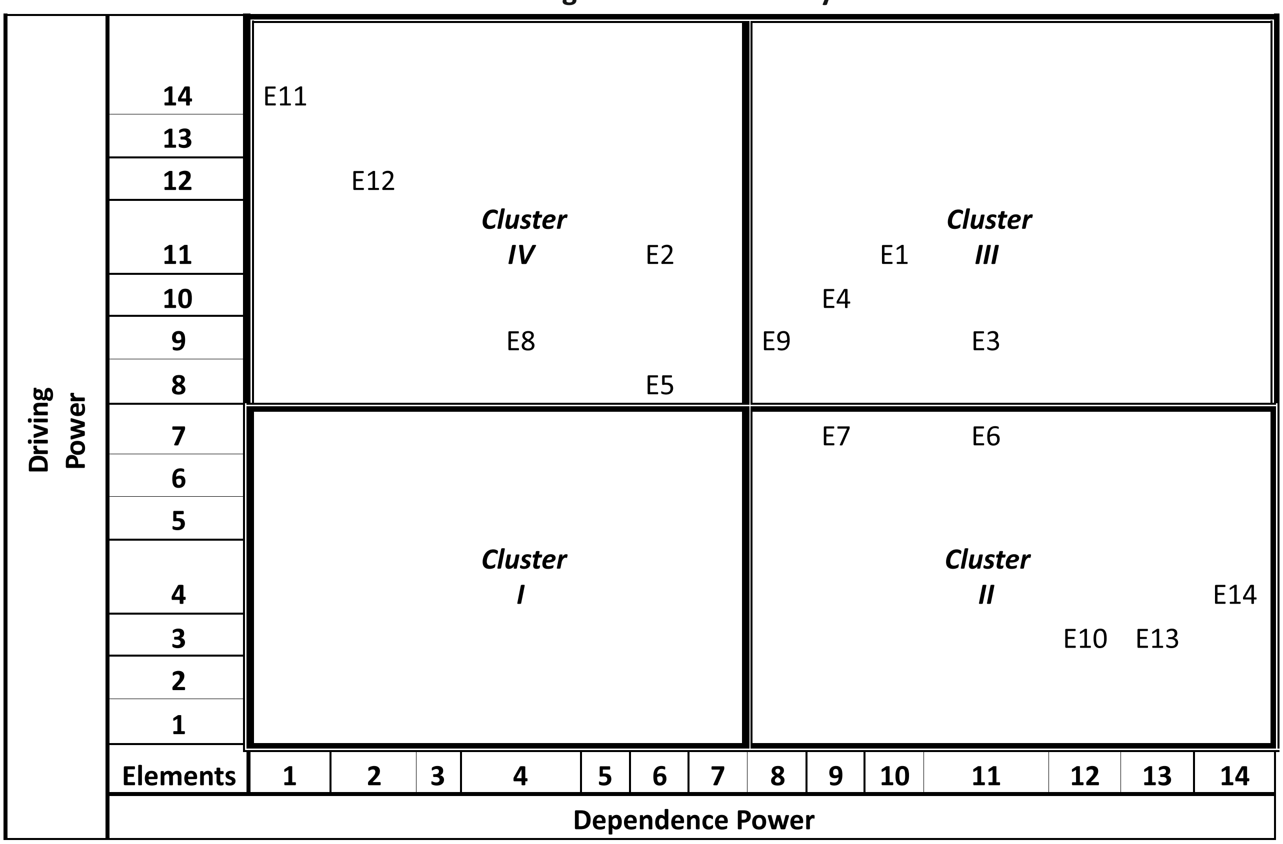
MICMAC Analysis

The expansion of MICMAC is cross impact matrix multiplication applied to classification. The rationale of MICMAC is to identify and analyze the variables according to their driving and dependence power. This is to explore the key variables which drive overconfidence and on which the behavioral trait of overconfidence is

Table 7. MICMAC Analysis

Elements	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Driving Power	Rank
1	1	1	1	1	1	1	1	0	1	1	0	0	1	1	11	III
2	1	1	1	1	1	1	1	0	1	1	0	0	1	1	11	III
3	1	0	1	1	1	1	1	0	1	1	0	0	0	1	9	V
4	1	0	1	1	0	1	1	1	1	1	0	0	1	1	10	IV
5	1	0	1	1	1	1	0	0	0	1	0	0	1	1	8	VI
6	1	0	0	1	0	1	1	0	0	1	0	0	1	1	7	VII
7	1	0	1	0	0	1	1	0	0	1	0	0	1	1	7	VII
8	0	1	1	0	0	1	1	1	1	1	0	0	1	1	9	V
9	1	0	1	1	0	1	0	0	1	1	0	0	1	1	8	VI
10	0	0	0	0	0	0	0	0	0	1	0	0	1	1	3	IX
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14	I
12	0	1	1	1	1	1	1	1	1	1	0	1	1	1	12	II
13	0	0	1	0	0	0	0	0	0	0	0	0	1	1	3	IX
14	1	1	0	0	0	0	0	0	0	0	0	0	1	1	4	VIII
Dependence Power	10	6	11	9	6	11	9	4	8	12	1	2	13	14		
Rank	V	VIII	IV	VI	VIII	IV	VI	IX	VII	III	XI	X	II	I		

Figure 2. Cluster Analysis



dependent. The Table 7 depicts the framework for driving and dependence power on the basis of their 1s in rows and columns.

When all the variables are placed according to their rank, both in driving power and dependence, a graph is prepared on the basis of four clusters. For example, Elements 11 and 12 have first rank in drivers ; whereas, Elements 10 and 11, respectively have the first rank in dependence ; so, as per the powers, they are to be placed in the area of four clusters. Four of the clusters are explained in the Figure 2 :

★ **Cluster 1:** This zone is known as autonomous variables. They have weak driving and dependence power which led them to disconnect from the whole process. However, few strong links might be available. In this situation, none of the elements fall under the cluster of autonomous variables.

★ **Cluster 2:** This cluster is known as dependent variables. These are imbibed with weak driving power and strong dependence power. Element 6, 7, 10, 13, and 14 are in this cluster, which are strong in dependence. These are also known as resultant and output variables, which are strongly influenced by linkage and influential variables.

★ **Cluster 3:** These are linkage variables, which are strong both in driving and dependence power. These are highly unstable as they affect changes in other variables, and alongside, get affected by changes in the rest of the variables of other clusters. Element 1, 4, 3, and 9 are in this category, which are unstable.

★ **Cluster 4:** This cluster is an independent variable zone, which is also known as the influential variable. These are high in driving power but low in dependence. Element 2, 5, 8, 11, and 12 fall in this category. These are the key objective criteria of the whole process.

Research Implications and Conclusion

The robust factors of overconfidence bias and its impact were analyzed with the help of the ISM methodology. The hierarchical relationship shows that the pseudo feeling of beating the market along with the available amount of information, the illusion of knowledge, investment experience, and rising trend in the market (bull market) enhances the level of confidence. These factors are considered as agile variables due to which investors incorrectly measure their caliber of skills, which lead them to feel that they are better than others, and this results in frequent trading and trading practices in volume. The mispricing of security lined up with price distortion ultimately ends up with undiversification of a portfolio, underestimation of risk, and reduced turnover or earnings, which eventually upshot poor portfolio performance.

The robustness of the investors' overconfident behavior has to be managed. In this direction, the available information should be used rationally. The investors must analyze the information from all the angles rather than following it blindly. If they get any public information, they must give ear to the news and not just overestimate their private signals of information. In this series, past experience shapes the learning curve, and investors must learn from their past mistakes in place of making wrong decisions every time.

Limitations of the Study and the Way Forward

The present study has promisingly focused on complexities to understand the dynamics of overconfidence bias in the stock market. The issues in other biases may slightly differ from this bias as confounding of related biases could give different results. The ISM model is highly dependent on the experience and judgment of the expert team. The model developed using ISM needs to be validated. The field of behavioral finance is evolving and in context of behavioral finance biases, a number of research propositions may be proposed and research relating to the modeling can be done for resolving complex issues. It would be a light house to the investors and brokers for understanding the investment dynamics which are surrounded with varied behavioral anomalies.

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