Mitigating Investor Overconfidence: Insights from Behavioral Finance with Reference to the Colombo Stock Exchange

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Abstract

The behavioral finance literature shows that investors are inclined to behavioral biases in their investment decisions. As one of such behavioral biases, overconfidence bias has been a widely studied phenomenon in the literature, revealing its adverse consequences on investment decision making and efficient functioning of financial markets. However, the literature still does not sufficiently explain on how investors can mitigate it when making their investment decisions. Hence, based on the evolutionary perspective predicted by the Adaptive Market Hypothesis Theory, this study attempts to explore on what cognitive, affective, social and behavioral mechanisms mitigate individual investors' overconfidence judgments in their stock investment decisions. A sample of individual investors of the Colombo Stock Exchange was surveyed through a self-administrated questionnaire to collect data, the analysis of which was conducted using the PLS-SEM. The results suggest that the investors learn about their overconfidence bias through the self-reflection on their past investment experiences. However, the extent of the self-reflection tends be low since it is not strengthened through investors' desire for learning and their relationships with investment advisors and other investors, which could be attributed to the market uncertainties existed during period of the study. The findings of the study contribute to theory and practice in the context of individual investors' decision-making.

Keywords: Adaptive market hypothesis, Learning behavior, Investor education, Overconfidence bias, Self-reflection, Transformative learning.

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Introduction

It is widely believed that capital markets play a pivotal role in an economy by serving as a powerful driver for both economic growth and wealth creation since they mainly facilitate for investment, efficient allocation of capital, risk management, discovering prices, providing liquidity, and supporting job creation. Their ability to mobilize savings and channel them into productive investments fuels innovation, fosters entrepreneurship, and enhances overall economic prosperity. Thus, efficient functioning of capital market is paramount important to an economy, which, among many factors and forces, is affected by behavior of market participants.

The behavioral finance theories and empirical findings often show that financial market participants behave irrationally since their rationality is bounded by variety of factors from different dimensions (for example, cognitive limitations, psychological factors, social and cultural influences, information asymmetry). It results in mispriced securities, thereby, inefficient capital markets (Barber & Odean, 2013; Gokhale et al., 2015; Shefrin, 2002; Zahera & Bansal, 2018). Particularly, in case of a stock market, the literature largely reveals that individual investors exhibit irrational behaviors (also known as "behavioral biases") in their decision making (Mittal, 2022). On the contrary, the adaptive market hypothesis (AMH) theory (Lo, 2004, 2005, 2012) predicts an evolutionary perspective for investors' behavior, suggesting that investors are capable of learning about biases and adapting to market conditions over time. Accordingly, it can be expected that they are able to minimize biases over time through a learning process.

This study concerns on overconfidence bias, one of the behavioral biases that affects the stock investment decisions of individual investors (Mittal, 2022). It is a cognitive bias leading to excessive investment and trading by investors in financial markets (Grežo, 2021), which adversely affect the performance of their investments (Barberis & Thaler, 2003; Che Hassan et al., 2023; Cao et al., 2021; Filbeck et al., 2017; Hirshleifer, 2015). Although, overconfidence attitude is a widely studied phenomenon, according to my knowledge, the literature still does not sufficiently explain on how individual investors can mitigate or get rid of it in their investment decisions. Accordingly, this study attempts to explore on what cognitive, affective, social and behavioral mechanisms mitigate individual investors' overconfidence judgments in their stock investment decisions. Concerning the evolutionary perspective predicted by the AMH theory, it hypothesizes that investors are capable of learning their overconfidence bias over time and mitigating it when they make subsequent investment decisions.

The model of investor learning behavior proposed by Shantha et al. (2018) was adopted to conceptualize the learning behavior and examine its effect on overconfidence bias. A sample of individual investors of the Colombo Stock Exchange (CSE) was surveyed through a web-based self-administrated questionnaire during the period of January-March 2023 to collect data, the analysis of which was conducted by using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique to examine the study hypotheses. The results show that the investors learn about their overconfidence bias through the self-reflection of their past investment experiences. However, the extent of the learning seems be low since it is not strengthened through investors' desire for learning and their relationships with investment advisors and other investors, which could be attributed to the market uncertainties existed during period of the study.

This study will contribute to academia and practice as follows. It contributes to the overconfidence literature by integrating and analyzing the cognitive, affective, social and behavioral aspects that are integral to learning behavior of an individual investor in mitigating his/her overconfidence judgments in stock investment decisions. This study is also the first of this kind, providing empirical evidence on how learning occurs in an individual investor to mitigate his/her overconfidence bias. For practitioners, this study recommends a learning approach that should be fostered among the individual investors to minimize their overconfidence attitude, thereby, the associated negative consequences to their wealth. The findings of this study can also be adopted by stock exchanges and investment advisors when designing training programs for the individual investors. Further. the individual investors can apply the implications of this study to improve their sophistication in order to enhance their investment performance.

The rest of the paper is organized as follows. Section 2 reviews literature on overconfidence bias and learning behavior to mitigate it. The research methodology is detailed in section 3. Section 4 discusses the respondents' demographic and behavioral characteristics, the measurement quality of the constructs of the conceptual model used in the study, and hypothesis testing results. Section 5 concludes the paper with its theoretical and practical implications, and areas for future research.

Literature Review and Hypotheses

Overconfidence Bias and Its Causes

Overconfidence indicates an individual's unwarranted confidence in his/her intuitive reasoning, judgments and cognitive abilities (Pompian, 2006). Daniel et al. (1998) define an overconfident investor as 'one who overestimates the precision of his private information signal, but not of information signals publicly received by all'. According to their model, investors, by observing the outcomes of their trading, appraise their own trading ability in a biased manner. They tend to attribute too strongly the events that confirm the validity of their actions to their high ability, and the events that disconfirm the validity of their actions to the external noise. Consequently, they overestimate the ability to generate information and become overconfident about their private information as compared to public information. Then, this overconfidence overweighs the private information relative to public information in their subsequent trading decisions.

Overconfidence can be explained through a well-documented psychological theory known as attribution theory (Weiner & Weiner, 1985). This theory highlights the tendency to attribute personal successes to one's own abilities while blaming failures on external factors. The attribution theory divides this biased behavior into two categories, namely self-enhancement bias and self-protection bias (Campbell & Sedikides, 1999). Self-enhancement bias involves attributing successes to oneself, whereas self-protection bias involves diverting blame for failures onto external factors. Psychological literature suggests these biases stem from either motivational or cognitive reasoning (Shepperd et al., 2008). Motivational reasoning encompasses the desire for self-enhancement and self-presentation, which drive individuals to attribute successes to themselves to maintain a positive image. Cognitive reasoning, on the other hand, involves the mental evaluation of achievements.

Consistent with the attribution theory, the studies conducted by Barber & Odean (2013), Gervais & Odean (2001), and Ishfaq et al. (2020) show that overconfidence often stems from biased self-attribution, which hinders individuals from accurately assessing their own abilities. For example, Gervais & Odean (2001) found that traders who correctly predict future dividends often mistakenly attribute their success to their own skill, leading to increased overconfidence. Particularly, in the context of the CSE of Sri Lanka, previous studies consistently reveal that overconfidence bias impacts on investment decision making, thereby investment performance (Kengatharan & Kengatharan, 2014; Lasantha & Kumara, 2021; Ranaweera & Kawshala, 2022; Siraji, 2019). Notably, the study by Perera & Gunathilaka (2022) on the CSE reveals that individual investors are susceptible to biased self-attribution and thereby, overconfidence bias due to their tendency to inaccurately evaluate investment alternatives.

The behavioral finance literature has also recognized investment experience as a fundamental determinant of overconfidence bias of investors. It reveals both positive and negative effects of investment experience on overconfidence bias in investment decisions. The positive effect is expected based on the belief that investors accumulate knowledge and skills over time, hence, are less prone to overconfidence bias as they become more experienced in investing (Dhar & Zhu, 2006; Feng & Seasholes, 2005; List, 2011; Nicolosi et al., 2009). Supporting this prediction, Gervais & Odean (2001), Koestner et al. (2017) and Menkhoff et al. (2013) find that overconfidence bias declines with the experience. On the contrary, Bhandari & Deaves (2006), Deaves et al. (2010), Glaser & Weber (2007), Kirchler & Maciejovsky (2002), Mishra & Metilda (2015) and Xiao (2015) reveal that the investors who are more experienced, are prone to overconfidence bias to a greater extent. The studies of Baker et al. (2019) and Chen et al. (2007) also find that the experienced individual investors demonstrate higher level of overconfidence relative to the inexperienced investors. Accordingly, the previous studies have primarily focused on identifying the causes of overconfidence bias among investors as well as its impact on investment decision making and performance. However, the strategies for mitigating this bias have not been adequately explored.

Mitigating Investor Overconfidence

Based on the concept of bounded rationality and principles of evolutionary biology, Lo (2004, 2005, 2012) introduced a new perspective called "Adaptive Market Hypothesis" to explain decision making behavior in a dynamic market environment. It states that 'individuals make choices based on past experience and their best guess as to what might be optimal, and they learn by receiving positive or negative reinforcement from the outcomes' (Lo, 2004). Accordingly, the theory implies an experiential learning process, which means that investors learn about their biases from their experiences and, thereby, adapt to market environment over time. However, in view of these mixed results indicated by previous studies relating to this experience-based learning hypothesis, Shantha et al. (2018) argue that past investment experiences do not merely produce learning effects to minimize behavioral biases. Consistent with the transformative learning theory of Mezirow (1994), the learning effects occur when the experiences are cognitively reflected upon (known as 'self-reflection'), which involves cognitive evaluation about the validity of mental frames (for example, beliefs, thoughts and assumptions) underlying the past decisions by reflecting upon the associated experiences (Mezirow, 2018). It enables the investors to appropriately revise biased mental frames leading to their behavioral biases. Thus, it can be expected that a higher investment experience leads to a higher level of self-reflection to reduce overconfidence bias. Accordingly, it is hypothesized that the investment experience (IE) reduces overconfidence bias (OC) through the mediation effect of self-reflection (SR), as indicated by the hypothesis 1 below.

Hypothesis 1 (H1): IE reduces OC bias through the mediation effect of SR.

In addition to this cognitive aspect of learning, Shantha et al. (2018) predict that investors' affective states strengthen their learning process. Since the learning process in this case is a self-regulated one, affective phenomena such as investors' emotions, interest, attention to mistakes, boredom, and frustration are integrated with their cognitive functioning, influencing their desire for learning (Isen, 2000). For instance, a positive mood can enhance creativity and flexibility in learning, while interest and attention are likely to stimulate active exploration of information (Lovric et al., 2008; Picard et al., 2004). Conversely, investors who are frustrated, depressed, disinterested, or inattentive cannot be expected to engage in learning efficiently. Based on critical reviews of the transformation learning theory and its empirical findings, Taylor (2000, 2007) also suggests that the desire to learn strengthens cognitive functioning during the reflective process. Accordingly, it is hypothesized that investors' desire for learning (DL) moderates the positive relationship between IE and SR, as indicated by hypothesis 2 below.

Hypothesis 2 (H2): An investor's DL positively moderates the positive relationship between IE and SR.

Further, Shantha et al. (2018) predict that investors' social relationships can strengthen their self-reflection, which is consistent with the learning literature, as follows. Koole et al. (2011), by reviewing factors confounding self-reflection, show that social interactions enhance the reflection process by creating a stimulating environment where learners can understand the meanings of their experiences and receive feedback on their behaviors. Proposing a practice-based model of transformative learning, Nohl (2015) also indicates that external feedback can either confirm or challenge interpretation of experiences, guiding toward a more effective learning path. Accordingly, social relationships facilitate investors to acquire necessary information and practical knowledge for perspective transformation. Particularly, trustworthy relationships enhance confidence in the knowledge and information received, thereby increasing their tendency to engage in self-reflection (Taylor, 2007). Thus, consistent with Shantha et al. (2018), it is hypothesized that investors' authentic relationships with their investment advisors (ARAD) and authentic relationships with other investors (AROT) moderate the positive relationship between IE and SR, as indicated by the hypotheses 3 and 4 below.

Hypothesis 3 (H3): An investor's ARAD positively moderates the positive relationship between IE and SR.

Hypothesis 4 (H4): An investor's AROT positively moderates the positive relationship between IE and SR.

Figure 1 depicts the conceptual model of the study with the associated hypotheses.

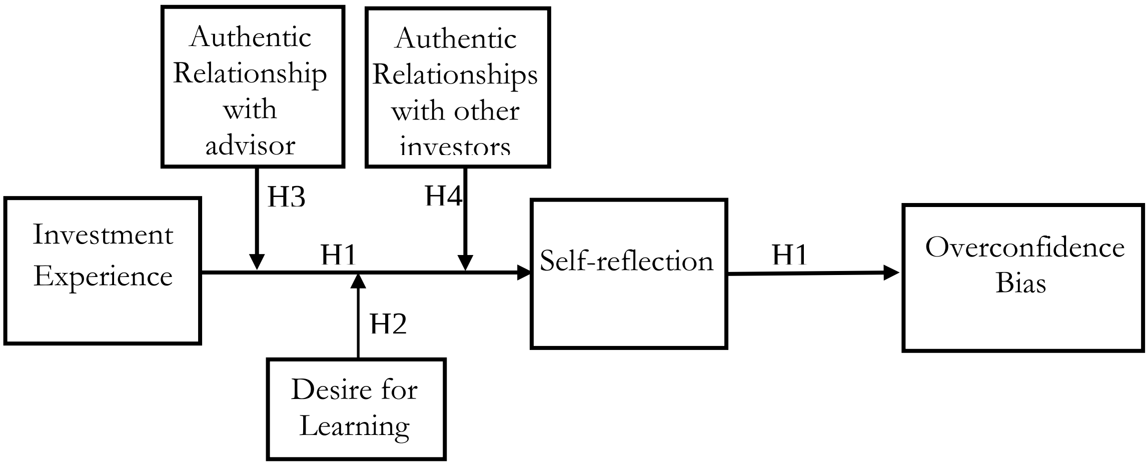

Figure 1. Conceptual Model of Individual Investors' Learning Behavior
(Adopted from Shantha et al. (2018))

Methodology

Collection of Data

The analysis unit of this study is the individual investors of the CSE who have active security accounts over the last six months. The data was collected from a web-based self-administrated questionnaire survey during the period of January-March 2023. Sample of 1000 investors was surrey to survey by emailing the web link of the questionnaire. However, only 395 valid responses were received, which represents a response rate of 39.5%. During the data collection period, the investors were frustrated due to market uncertainties and associated unfavorable consequences. Hence, they may become less motivated for responding to the questionnaire, which could mainly account for this lower response rate. However, the responses received appear to be free of non-response bias since the examination of which, based on the procedure suggested by Dooley & Lindner (2003), finds no significant difference between early and late responses.

Questionnaire Design

The questionnaire designed for the study consisted of items to obtain information on the respondents' demography and investment characteristics, and for the measurement of the constructs of the conceptual model. Consistent with the suggestions of Podsakoff et al. (2012), the following procedures were used to alleviate the common method bias. As detailed in the following paragraph, all the constructs of the model were measured using the validated scales available in the literature with modifications to their phrasing to suit the study. To minimize respondents' anxiety, the question items of each construct were presented in a separate section of the questionnaire with different sets of instructions to pursue. The respondents were also assured that their responses were neither right nor wrong and kept anonymous. Further, the content and face validity of questionnaire was tested in a pilot study with a sample of 30 individual investors. Moreover, meaning and phrasing of the question items and the instructions given for responding to the questionnaire were discussed with three investment advisors and three academics to further enhance their clarity. Harman's one-factor test also finds that the responses received are free of common method bias.

The scales for measuring the model's constructs were adopted from literature, as discussed below. IE of the respondents was measured in terms of the number of years during which they had been investing in the stock market since it is the most commonly used method in the previous behavioral studies concerning on the individual investors (See, for example, Abreu & Mendes, 2012; Mishra & Metilda, 2015; Seru et al., 2009; Yalcin et al., 2016). Kember et al. (2000) proposed a scale to measure the extent of self-reflection that an individual engages in learning. It consists of three levels of self-reflection known as content, process, and premise reflections. In view of the extent of self-reflection required to minimize overconfidence bias, it is believed that the awareness of experience (content reflection) is not simply adequate for learning. A learning attempt rather succeeds when the experience leads to changing an investor's way of thinking, feeling and acting (process reflection) and identifying biases, and appropriately revising the associated mental frames (premise reflection). Accordingly, the extent of SR was assessed by three items relating to the process reflection and four items relating to the premise reflection. Relying on the scales developed by Yalcin et al. (2016) and those adapted in the study conducted by Baker et al. (2019), OC was measured through four items. The investors' desire for learning was measured based on the self-directed learning readiness scale proposed by Fisher et al. (2001). Their scale initially comprised of 12 items to assess the desire for learning. Nevertheless, Fisher & King (2010) and Williams & Brown (2013) support for a 10-item scale since it indicates a better model fit relative to the initial 12-item scale. Thus, DL construct was measured using these 10 items which, however, was reduced to eight items since two items were excluded from the analysis due to low factor loading found by indicator relevance test procedures (Sarstedt et al., 2017; Wong, 2016). Based on the scale used by Kale et al. (2000), the measurements of ARAD and AROT were consisted of five items each. However, one item was dropped when measuring ARAD due to low factor loading.

Data Analysis

This study aims to explore how learning occurs within the individual investors to minimize their overconfidence bias. Becker et al. (2013), Evermann & Tate (2016) and Sarstedt et al. (2017) recommend to apply the PLS-SEM when the research goal is to predict a target construct by identifying its relevant antecedents, since the higher statistical power of the PLS-SEM is suitable for an exploratory research design. When concerning on the research setting of this study, the conceptual model is consisted of many constructs and many indicator items to measure each of those constructs, the sample size is small, and the theory is less developed for predicting the target constructs. In such circumstances, the PLS-SEM is suggested to be more appropriate than the factor-based SEM as it works efficiently with small sample sizes and complex path models, and does not require to meet the parametric distributional assumptions

(Sarstedt et al. (2017), Hair et al. (2017), and references therein). Accordingly, the PLS-SEM technique is applied for the analysis with the support of SmartPLS 3 software.

Sarstedt et al. (2014) suggest a two-step procedure for applying the PLS-SEM. First, the measurement model is assessed to confirm the measurement quality of the constructs. If the measurement quality is supported, then, the structural model is evaluated in the second step. Following this procedure, since the constructs were reflectively defined, the indicator reliability, internal consistency reliability, convergent validity, and discriminant validity tests were carried out to evaluate their measurement quality. When evaluating the structural model in the second step, it was first checked for multicollinearity issues by conducting the variance inflation factor (VIF) analysis. After that, its predictive capabilities, as indicated by coefficient of determination (R^2), cross-validated redundancy (Q^2) and effect-size (f^2) criteria, were reviewed, and the hypotheses were tested based on the relevance and significance of path coefficients. In this step, the estimation of Q^2 was based on the blindfolding procedure with an omission distance of six (Hair et al., 2017). f^2, being the size of the effect of a particular predictor variable on its endogenous variable, was estimated through the procedure suggested by Henseler & Chin (2010).

Results and Discussion

Demographic and Behavioral Characteristics of the Respondents

The demographic and behavioral characteristics of the respondents are analyzed and shown in Table 1. Of the participants to the survey, 71.4 percent are male investors. Considerably, a lower proportion of female responses is unsurprising since the investment decisions are mostly made by male in the Sri Lankan culture. In addition, the proportion of respondents who are below the age of 35 years is 41 percent, while about 44 percent is in the age range of 35-54 years.

Table 1. Demographic and Behavioral Characteristics of Survey Respondents

Profile	Group	No. of Respondents	%
Gender	Male	282	71.4
	Female	113	28.6
Age	< 25 years	28	7.1
	25–34	134	33.9
	35–44	96	24.3
	45–54	79	20.0
	55 or above	58	14.7
Marital Status	Married	274	69.4
	Unmarried	121	30.6
Education	A/L	92	23.3
	Diploma	96	24.3
	Degree	123	31.2
	Postgraduate Diploma	21	5.3
	MBA/MSc	63	15.9
	Ph.D	0	0.0
Occupation	Private sector employee	308	78.0
	Public sector employee	20	5.1
	Retired	23	5.8

	Self-employed	34	8.6
	Unemployed	10	2.5
Investment experience	2 years or less	18	4.6
	3–7 years	97	24.7
	8–12 years	166	42.0
	13–17 years	71	18.0
	18 years or above	43	10.8
Trading frequency	Occasionally	234	59.2
	Once a month	37	9.4
	Once a week	38	9.6
	2–3 times a week	50	12.7
	Daily	36	9.1
Risk Appetite	Very low risk taker	54	13.7
	Low risk taker	130	32.9
	Average risk taker	90	22.8
	High risk taker	111	28.1
	Very high risk taker	10	2.5
Proportion of wealth invested in stocks	Less than 5%	77	19.5
	5–15%	192	48.6
	16–25%	53	13.4
	26–40%	23	5.8
	41–60%	33	8.4
	More than 60%	17	4.3

Source: Author's compilation

Further, in terms of the education level, almost a half of the respondents holds bachelor's degree or higher education qualification. Then, concerning on the occupation, private sector (78 percent), public sector (5.1 percent) and self-employed (8.6 percent) investors as well as retired (5.8 percent) and unemployed (2.5 percent) investors have participated to the survey. Therefore, the respondents seem to characterize fairly the demography of the individual investor population in the CSE.

The average investment experience of the respondents is 11 years (standard deviation 6.2). The sample represents a combination of high-experienced investors (10.8 percent having 18 years or more experience) and low-experienced investors (4.6 percent having 2 years or less experience). Concerning on the trading frequency, only 9.1 percent of the respondents trade stocks daily, while the majority of them trades occasionally. In terms of the attitudes towards risk, nearly a half of the sample possesses low risk appetite, whereas about 30 percent of the respondents exhibit high risk-taking behavior. In addition, most of the respondents show a lower tendency to invest in stocks, as evidence by 19.5 percent holding less than 5 percent of their wealth and 48.6 percent holding 5–15 percent of wealth in stocks. These investment attitudes may be due to the uncertain investment environment in the CSE over the last few years, which occurred mainly through the effect of economic crisis, political instability and COVID 19. With the uncertainty and associated down-market trends, investors may have experienced significant losses of their investment value, hence, become frustrated and panic for further losses. Consequently, they tend to behave more risk-aversely by shifting their stock investments to safer securities, which, then, results to a lower stock trading frequency. The mean value of overconfidence bias is 3.493. The values greater than 3 indicate that the respondents are prone to overconfidence in their stock investment decisions.

Measurement Quality of the Model's Constructs

The constructs' measurement quality was assessed in terms of their reliability and validity based on the measures as reported in Appendix 1. After conducting the indicator relevance test procedures (Sarstedt et al. 2017; Wong, 2016), the indicator items of all the constructs exhibit a satisfactory level of reliability for an exploratory study (Hulland, 1999). The cronbach's alpha and composite reliability values are larger than 0.7, which mean the internal consistency reliability of the respective constructs (Gefen et al., 2000; Nunnally & Bernstein, 1994). All the constructs also possess AVE of above 0.5, confirming their convergent validity. The Fornell and Larcker criterion and Heterotrait-monotrait (HTMT) criterion were examined to ensure the discriminant validity of the constructs. As shown in Appendix 1, the square root of AVE of all the constructs are larger than their correlation values with other constructs (Fornell & Larcker, 1981). The HTMT ratios are below 0.85 (Henseler et al., 2015). Accordingly, there appears to be a strong support for the discriminant validity of the constructs. In addition, the multicollinearity issues are not evident in the model since the VIF values are lower than five (Cassel et al., 1999; Hair et al., 2011).

Hypothesis Testing for Exploring the Effect of Learning on Overconfidence Bias

Figure 2 summarizes the key findings relating to the learning behavior hypothesized in this study. The variance explained (R^2) in SR and OC constructs are respectively 37.5% and 9.0% respectively. Q^2 values of SR and OC constructs are larger than zero, which mean an acceptable level of predictive accuracy of these constructs (Sarstedt et al., 2017). Tables 2 and 3 present the estimates of path coefficients, their significance and f^2 effect sizes to examine the hypotheses relating to the learning behaviors, which are discussed in the following sections.

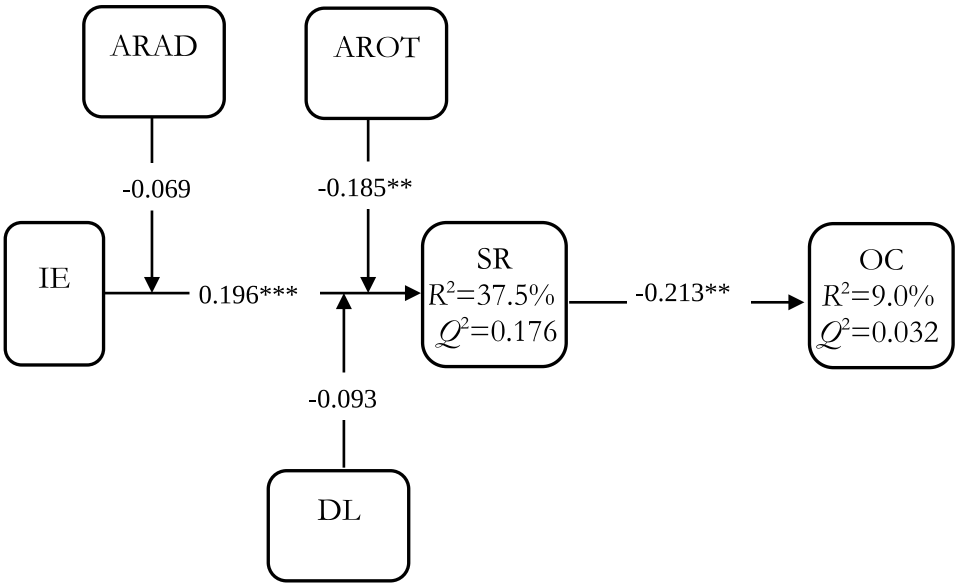

Figure 2. Key findings of Learning Behaviors of the Investors

Note: The significance at 1 percent, 5 percent and 10 percent levels are represented by ***, ** and * respectively.

The results, given in Panel A of Table 2, show that IE has positive impact on SR ($p<0.01$). The extent of this effect is an increase of SR by 0.196 standard deviation units for one standard deviation unit of IE, which, however, appears to be small, as reflected by f^2 of 0.051. The findings also reveal that SR has negative impact on OC ($p<0.05$). An increase of one standard deviation unit of SR decreases OC by 0.213 standard deviation units, which seem to be a small effect as reflected by its f^2 value. In addition, supporting H1, SR mediates the relationship between IE and OC ($p<0.10$). Since the direct effects of IE on OC is not evident, SR has full mediation effects on the relationship between IE and OC (Zhao et al., 2010). These findings are similar to those of Shantha (2019) on the CSE, which reveal a full mediation effect of self-reflection on the relationship between the experience and herd bias. Accordingly, it is evident that, not just past investment experiences of the investors, but self-reflection upon the experiences reduce their overconfidence bias. It means that the biases do not get minimized when the self-reflection is absent, and for a given level of experience, a higher level of self-reflection results to a lower level of biases. However, the magnitude of this learning effect appears to be low during the period of the study due to the investors' lesser tendency to involve in the self-reflection, as reflected by the small effect sizes of f^2 values discussed above. The market uncertainties prevailed during the study period could be considered as one of more likely reasons for the investors' lessor tendency to involve in self-reflection. As detailed in Section 3.1, investors were frustrated and, hence, reduced their stock holding in response to the uncertainties observed during this period. Consequently, they might not have had much interest in the self-reflection of their past experiences. In addition, the small size effect associated with the self-reflection can be attributed to the absence of strengthening it through investors' desire for learning and their relationships with investment advisors and other investors during the study period, which is detailed in the following paragraph.

Table 2. Examination of the Hypotheses on Learning Behavior.

Hypothesis	**Path**	**Path coefficient**	**Standard error**	***t*-statistic**	***p*-value**	f^2
Part A: Effect of IE on SR and OC						
H1	IE→SR	0.196	0.069	2.686	0.004***	0.051
	SR→OC	-0.213	0.111	1.953	0.025**	0.047
	IE→SR→OC	-0.043	0.027	1.467	0.071*	
	IE→OC	0.141	0.183	0.775	0.219	
Part B: Moderating effect of DL on SR						
H2	DL×IE→SR	-0.093	0.104	0.907	0.182	0.007
	DL×IE→SR→OC	0.021	0.028	0.738	0.230	
Part C: Moderating effect of ARAD on SR						
H3	ARAD×IE→SR	-0.069	0.086	0.836	0.202	0.005
	ARAD×IE→SR→OC	0.017	0.023	0.675	0.250	
Part D: Moderating effect of AROT on SR						
H4	AROT×IE→SR	-0.185	0.092	2.051	0.020**	0.028
	AROT×IE→SR→OC	0.039	0.029	1.409	0.079*	

Note: This table presents the results relating to the individual learning behavior, as hypothesized by H1 through H4. The significance at 1 percent, 5 percent and 10 percent levels are denoted by ***, ** and * respectively. f^2 represents the effect-size of the path's predictor variable on its endogenous variable. As a rule of thumb, f^2 values greater than 0.02, 0.15, and 0.35 indicate for small, medium and large effects respectively (Cohen, 1988; Sarstedt et al., 2017).

Source: Author's estimation

The moderating effects hypothesized in H2, H3 and H4 concern on the strengthening of the self-reflection. The estimates in parts B of Table 2 reveal that DL has no moderating effect on the relationship between IE and SR, as hypothesized by H2. However, the results presented in Table 3 shows that it has a direct positive impact on SR ($p<0.01$, $f^2=0.162$), which, in turn, has negative impact on OC ($p<0.05$). Hence, consistent with the findings of Shantha (2019), the results imply that desire for learning should be a direct predictor of self-reflection in the learning process. Further, according to Panel C of Table 2, ARAD has no positive moderating effects on the relationship between IE and SR. It may be due to decline in the investors' interactions with their investment advisors during the study period. As discussed in section 4.1, most of the respondents are characterized by having low risk appetite, low stock holding and infrequent trading behaviors since they were mostly frustrated and panic with the down-market trends and the associated losses occurred during this uncertain period. Consequently, their interactions with investment advisors might become weaken, which, in turn, impaired both amount and confidence of information and guidance that they receive for investing. Hence, the moderating effect of ARAD, as hypothesized by H3, is not evident. Further, contrary to the hypothesis H4, Panel D of Table 2 shows that AROT has a negative moderating effect on the relationship between IE and SR ($p<0.05$, $f^2=0.028$), which increases OC ($p<0.10$). This negative moderating effect could be due to the dominance of unsophisticated investors in frontier markets such as the CSE. When the market conditions are uncertain, investors typically observe other investors' trades and communicate with them to obtain information for decision making. However, when it happens with those having inadequate competence in investing, the self-reflection may become weakened and, consequently, biases would increase. In view of this, it is probable that AROT produces a negative moderating effect in the self-reflection process. According to these findings, it is evident that the self-reflection has not been strengthened through investors' desire for learning and their relationships with investment advisors and other investors during the study period.

Table 3. Effect of Desire for Learning on the Learning Behavior

Path	Path coefficient	Standard error	t-statistic	p-value	f^2
DL→SR	0.402	0.084	4.858	0.000***	0.162
DL→SR→OC	-0.088	0.050	1.772	0.038**	

Note: This table reports the direct effect of DL on SR and, thereby, on OC construct. The significance at 1 percent, 5 percent and 10 percent levels are denoted by ***, ** and * respectively. f^2 represents the effect-size of the path's predictor variable on its endogenous variable. As a rule of thumb, f^2 values greater than 0.02, 0.15, and 0.35 indicate for small, medium and large effects respectively (Cohen, 1988; Sarstedt et al., 2017).

Source: Author's estimation

Conclusions and Implications

This study explores on cognitive, affective, social and behavioral mechanisms that mitigate individual investors' overconfidence judgments in their stock investment decisions. Based on the implications of the AMH and the model of investor learning, proposed by Shantha et al. (2018), it attempts to claim that investors can minimize their overconfidence bias by involving in a learning behavior. Based on the findings, the study mainly concludes that the extent to which the overconfidence bias gets reduced depends, not merely on the level of investment experience that an investor has, but on the extent of the investors' involvement in self-reflection of their investment experiences when learning. As discussed in the following sections, while this study offers significant contributions to both theory and practice, it is essential to acknowledge its limitations. Recognizing these limitations is crucial for guiding future research efforts, which will enhance knowledge of how overconfidence bias is mitigated and facilitate the application of the findings in broader contexts.

Contribution to Theory

This study contributes to theory in several significant ways. First, the findings support the AMH, suggesting that investors can learn from their experiences and adjust their overconfidence bias over time, thereby improving their investment decisions in subsequent endeavors. This supports the dynamic nature of investor behavior as posited by the AMH, where market participants continuously evolve and adapt based on new information and feedback from their investment outcomes. Second, and perhaps more importantly, this study fills a critical gap in the literature by exploring into the mechanisms through which individual investors can mitigate their overconfidence bias in decision-making. To the best of our knowledge, this is the first attempt to comprehensively integrate cognitive, affective, social, and behavioral mechanisms in addressing overconfidence bias among individual investors. This holistic approach advances current literature by offering a comprehensive understanding of how various factors interact to influence investor behavior and thereby, mitigate overconfidence bias. Third, this study addresses a longstanding debate in the literature regarding the impact of investment experience on overconfidence bias. Contrary to the simplistic notion that experience alone reduces overconfidence, our results indicate that the cognitive reflection upon investment experiences is crucial in reducing overconfidence bias. This finding highlights the importance of reflective practice in financial decision-making, suggesting that investors must not only accumulate experience but also engage in thoughtful analysis of their past decisions to effectively mitigate overconfidence. Fourth, the results provide empirical support for the individual learning behavior hypothesized in the model of learning behavior proposed by Shantha et al. (2018). This empirical validation confirms the robustness and applicability of their model, demonstrating that learning behavior plays a critical role in shaping investment behavior.

Contribution to Practice

This study not only validates the theoretical model of learning proposed by Shantha et al. (2018), but also extends its applicability by showing how reflective practices can be operationalized to enhance investment decision-making, as follows. The results assist individual investors to aware how they can minimize overconfidence bias occurred in their investment decisions. Accordingly, the investors should engage in the self-reflection of their investment experiences to learn about overconfidence bias occurred with their previous investment attempts. It would enable them to appropriately revise their mental frames (beliefs, thoughts and assumptions) associated with overconfidence. In addition, investment advisors should apply the findings of the study to minimize their clients' overconfidence bias that impede their investment decisions. Based on the results of the study, they can commence educational initiatives to mitigate it. Accordingly, they would be able to provide more effective adversary service to their clients. Further, the understanding of investor learning behavior would be useful for stock exchanges to design awareness and training programs to promote the learning attempts among investors. It enables investors to avoid behavioral biases in their investment decision making, which would eventually facilitate for the development of stock exchange by minimizing unfavorable consequences such as bubbles and crashes and enhancing their efficient functioning. Accordingly, the findings of the study offer a more comprehensive framework for understanding and improving individual investors' decision-making and efficient functioning of a capital market.

Limitations of the Study and Future Research

This study has the following limitations. First, the study was conducted during a period of significant market uncertainty, which may have impacted investor sentiment and motivation to respond to the questionnaire. Hence, the data collection process and consequently, the study's findings are likely to have been influenced by the prevailing unfavorable market conditions. This temporal context limits the generalizability of the results to periods characterized by more favorable market conditions. Thus, future research should aim to replicate this study during periods of market stability or growth to validate the robustness and applicability of the proposed conceptual model under different market conditions. Second, the context of this study is the CSE, a frontier market characterized by the dominance of unsophisticated investors, infrequent trading, and higher uncertainty information and trading environments compared to developed and emerging markets. These unique characteristics of frontier markets limit the generalizability of the findings. To address this limitation, future research should replicate similar studies in developed and emerging markets, which would help confirm the robustness and applicability of the conceptual model across different market environments and investor profiles. Third, the study findings suggest that the desire for learning acts as a direct predictor of self-reflection rather than serving as a moderating variable. This insight necessitates a reevaluation of how individual learning behavior is modeled in the context of stock trading. Future research should incorporate the study's findings into the development of more refined models of individual investors' learning behavior and explore other factors that might influence or moderate the investors' self-reflection.

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Appendix 1: Assessment of Reliability and Validity of the Measurement Model and Multi-collinearity Issues

Measurement of Model's Constructs and their Reliability and Convergent Validity

Construct	Indicator Item	Indicator Loading	Cronbach's Alpha	composite reliability	AVE
Overconfidence (OC)	OC_1	0.707	0.874	0.811	0.532
	OC_2	0.813			
	OC_3	0.888			
	OC_4	0.423			
Self-reflection (SR)			0.867	0.884	0.526
	SR_1	0.594			
	SR_2	0.564			
	SR_3	0.812			
	SR_4	0.819			
	SR_5	0.638			
	SR_6	0.816			
	SR_7	0.781			
Investment Experience (IE)	TradeYrs	1.000	1.000	1.000	1.000
Desire for learning (DL)			0.912	0.928	0.618
	DL_1	0.800			
	DL_2	0.820			
	DL_3	0.807			
	DL_4	0.828			
	DL_5	---			
	DL_6	0.746			
	DL_7	0.732			
	DL_8	0.763			
	DL_9	0.787			
	DL_10	---			

Construct	Indicator Item	Indicator Loading	Cronbach's Alpha	composite reliability	AVE
Authentic relationship with investment advisor (ARAD)			0.874	0.891	0.671
	ARAD_1	0.869			
	ARAD_2	0.775			
	ARAD_3	0.813			
	ARAD_4	---			
	ARAD_5	0.817			
Authentic relationship with other investors (AROT)			0.870	0.887	0.613
	AROT_1	0.655			
	AROT_2	0.791			
	AROT_3	0.832			
	AROT_4	0.779			
	AROT_5	0.842			

Note: This table shows the indicator items and their loading, cronbach's alpha, composite reliability and average variance extracted (AVE) values for evaluating the measurement quality of each construct. An indicator is included in the model when its loading value is larger than 0.4 (Hair et al., 2013), which is also an acceptable level for an exploratory study (Hulland, 1999). Indicator relevance test procedures, suggested by Sarstedt et al. (2017) and Wong (2016), are conducted to decide whether the indicators with loading values between 0.4 and 0.7 should be retained in the model. --- indicates the deleted indicators based on this test. The cronbach's alpha and composite reliability values larger than 0.7 indicate the internal consistency reliability (Gefen et al., 2000; Nunnally & Bernstein, 1994). The AVE value greater than 0.5 represents the convergent validity (Bagozzi & Yi, 1988; Fornell & Larcker, 1981).

Fornell-Larcker Criterion Analysis for Assessing Discriminant Validity

	ARAD	AROT	DL	OC	SR	IE	Is discriminant validity met?
ARAD	**0.819**						Yes
AROT	0.428	**0.783**					Yes
DL	0.421	0.532	**0.786**				Yes
OC	-0.010	0.229	0.065	**0.730**			Yes
SR	0.333	0.306	0.543	-0.126	**0.726**		Yes
IE	0.101	0.171	0.185	-0.029	0.208	Single item	Yes

Note: This table presents a comparison between each construct's the square root of AVE value (as printed in bold in the diagonal) and its correlations with the other constructs for assessing the discriminant validity. A construct's discriminant validity is confirmed when its square root of AVE is larger than its correlation values with other constructs (Fornell & Larcker, 1981).

HTMT Criterion Analysis for Assessing Discriminant Validity

	ARAD	AROT	DL	OC	SR	IE
ARAD						
AROT	0.463					
DL	0.456	0.589				
OC	0.208	0.235	0.156			
SR	0.353	0.324	0.597	0.182		
IE	0.117	0.172	0.193	0.079	0.226	

Note: This table reports a construct's HTMT ratio of correlations with other constructs of the model. The discriminant validity of a construct is confirmed when these correlation values are less than 0.85 (Henseler et al., 2015).

Variance Inflation Factor (VIF) Analysis for Assessing Collinearity Issues

	ARAD	AROT	IE	DL	SR
SR	1.385	1.533	1.131	1.698	
OC		1.103			1.103

Note: This table presents the VIF values of exogenous constructs (given in the column) with respect to their endogenous constructs (given in raw wise) for the assessment of multicollinearity. The VIF value of 5 or above indicates collinearity issues (Cassel et al., 1999; Hair et al., 2011).