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Ecological Rational Behavior of Individual Investors in Stock Investment Decisions

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ABSTRACT

While heuristics are widely applied in decision-making, they can lead to biases and are therefore considered irrational behavior. However, the Adaptive Market Hypothesis implies that heuristics are neither rational nor irrational, and individuals should learn to use heuristics appropriate to the structure of the environment, which is referred to as *"ecological rational behavior"*. This study examines how individual investors can succeed using heuristics. Data was collected from 395 individual investors of the Colombo Stock Exchange through a questionnaire survey and analyzed using PLS-SEM. The findings indicate that reducing inappropriate heuristics depends on self-reflection of investment experience rather than the experience itself. Further, contrary to social learning, social conformity in response to market uncertainties increased the use of inappropriate heuristics in their decision-making.

Keywords: Adaptive Market Hypothesis, Colombo Stock Exchange, Information Processing Bias, Individual Learning, Investor Education, Social Learning

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"In order to succeed, you must fail so that you know what not to do the next time."

Anthony J. D'Angelo

INTRODUCTION

In standard finance, the Efficient Market Hypothesis (EMH) predicts that financial markets are efficient in adjusting new information to the prices of securities. One of the assumptions of EMH is that investors rationally make decisions, which involves objective and unbiased processing of all available information relevant to the decision. Hence, the efficiency status of a financial market can be expected to vary according to how investors process information when making their decisions. Investors may process information by applying simple heuristics (for example, following blog posts, analysts' recommendations and financial news, and stock screening based on simple criteria) as well as more complex rational analytical techniques (for example, technical analysis and fundamental analysis). However, when concerning individual investors whose behavior is typically bounded by cognitive and psychological limitations, time pressure, cost of information search and acquisition, limited attention, low level of financial literacy, and exposure to social influences, it is less likely that they would engage in an in-depth processing of all relevant information rationally, instead, would adopt simple heuristics in their investment decisions (Che Hassan et al., 2023; Filbeck et al., 2017; Khan et al., 2021; Singh, 2010).

The behavioral finance literature emphasizes that heuristics are widely applied since the conditions required for rational models (for example, knowledge of all relevant alternatives, their outcomes and probabilities, and predictable future) are rarely met in most of the decision-making contexts (Gigerenzer & Gaissmaier, 2011; Cao et al., 2021). However, decision-making based on heuristics could be prone to mistakes since the benefits of fast and frugal decisions occur at the cost of lower volume and quality of information processing, which means some important information may be ignored or underweighted when the decision is being taken. Supporting this view, the behavioral finance literature largely reveals that heuristic decision-making[1] is associated with information-processing biases[2], for example, conservatism, representativeness, and overconfidence, which could adversely affect the performance of an investment (Barberis & Thaler, 2003; Che Hassan et al.,

[1]A heuristic is a rule of thumb or mental short-cut, which, as compared to the rational methods, involves a lower amount of information processing, and requires lesser cognitive efforts. Thus, it facilitates fast and frugal decision making.
[2]Information processing biases are errors of thinking when processing information for making a financial decision.

2023; Filbeck et al., 2017; Hirshleifer, 2015). Accordingly, a question arises as to how an individual investor could succeed through such heuristic-driven decisions.

The adaptive market hypothesis theory (Lo, 2004; 2005; 2012), based on an evolutionary view, implies that investors are capable of learning about the information processing biases associated with heuristics over time and, thereby, choosing heuristics that are appropriate to the prevailing market conditions. Accordingly, heuristics are neither rational nor irrational, and individuals should learn to use heuristics appropriate to the structure of the environment, which is referred to as *"ecological rational behavior"* (Gigerenzer & Gaissmaier, 2011; Gigerenzer et al., 1999). Hence, investors are supposed to be ecologically rational to succeed in heuristic-driven investment decision-making. This paper concerns the ecologically rational behavior of individual investors when investing in stocks. It aims to explore how learning occurs within the individual investors to avoid the use of heuristics leading to information processing biases so that they are able to adapt to the prevailing market environment with appropriate heuristics.

In light of the above, this study is conducted on a frontier stock market, the Colombo Stock Exchange (CSE) of Sri Lanka for the following two reasons. First, the individual investors of a frontier market are generally considered to be more unsophisticated; consequently, their decisions would be largely affected by information processing biases compared to those of developed and emerging markets. Second, over the past few years, the investment environment of the CSE has been highly uncertain through instances of speculative bubbles and crash, effects COVID-19, and political uncertainty, and economic crisis situations in the country, which may also have motivated the investors to rely more on heuristics in their investment decisions (Gigerenzer & Gaissmaier, 2011; Lo, 2012; Raines & Leathers, 2011). Hence, the CSE appears to be an ideal market setting for this study. The model of investor learning behavior proposed by Shantha et al. (2018) was adopted to conceptualize the learning behavior and examine its effect on information-processing biases associated with heuristic decision-making.

The findings of this study will contribute to the academia and practice as follows. First, this study extends the theoretical framework of AMH, showing the learning processes that play a crucial role in minimizing biases. Second, it provides a new perspective to the long-standing puzzle of the effect of investment experience on behavioral biases occurring in investment decisions. Introducing the concept of self-reflection challenges the conventional belief that extensive investment experience alone is sufficient to reduce behavioral biases, suggesting that the quality of self-reflection is as important as the quantity of experience. This perspective provides a more comprehensive view of how experience shapes investor behavior in minimizing behavioral biases. Third, even though heuristic decision-making has been extensively studied in behavioral finance concerning its effects on investment performance and the functioning of financial markets (Che Hassan et al., 2023; Filbeck et al., 2017; Hirshleifer, 2015), studies on mechanisms to minimize the information processing biases associated with heuristics appear to be an unexplored behavioral issue in the literature. (Bílek et al., 2018; Che Hassan et al., 2023). Therefore, this study is the first of its kind, providing empirical evidence on mechanisms for minimizing information processing biases that arise with heuristic decision-making. It suggests a learning approach that should be encouraged among individual investors to minimize their information processing biases, thereby, the associated possible negative consequences to their wealth. Fourth, the stock exchanges and investment advisors can adopt the implications of this study when designing training programs for individual investors. Further, individual investors can also use the implications of this study to improve their sophistication so that their market participation and investment performance will be enhanced. Accordingly, the current study enriches the behavioral finance literature by providing an in-depth knowledge of the bias-learning process of an individual investor.

The remainder of this paper is organized as follows. Section 2 reviews literature on information processing biases associated with heuristic-driven investment decisions and learning behavior that could reduce such biases. The research methodology is presented in section 3. Section 4 details the demographic and behavioral characteristics of the respondents, examines the measurement quality of the model’s constructs and provides hypothesis testing results. Section 5 concludes the paper with its theoretical and practical implications.

LITERATURE REVIEW

Information Processing Biases Associated with Investment Decisions

The Efficient Market Hypothesis theorizes that investors make decisions rationally, which involves a deliberately engaged objective and unbiased processing of all available information relevant to their decisions. In contrast, the dual-process theory suggests that humans exhibit a strong propensity to avoid such deliberate information processing; rather, they prefer intuitive decision-making (Chaiken & Trope, 1999; Evans & Stanovich, 2013). Intuition is a rapid, automatic process that does not involve extensive analytical procedures and enables individuals to understand a situation or problem instantaneously. Intuitive insights often originate from the subconscious mind, where vast amounts of information and experiences are processed outside of conscious awareness by integrating past experiences, patterns, and knowledge to generate quick judgments or decisions (Evans & Stanovich, 2013).

The dual-process theory predicts that decision-making by intuition is frequently influenced by heuristics (Evans, 2016; Kahneman, 2012). For example, individual investors might follow blog posts, analysts' recommendations, financial news, and simple stock screening criteria in their trading decisions. However, decision-making based on heuristics is prone to errors since it bypasses rational information processing, leading to the neglect or under/overweighting critical information. Accordingly, given the fact that individual investors' behavior is typically constrained by their cognitive and psychological limitations, time pressure, the cost of information search and acquisition, limited attention, and social influences (Che Hassan et al., 2023; Filbeck et al., 2017; Khan et al., 2021), it is likely that they show a greater tendency to rely on intuitive decision-making rather than to deliberately engaged information processing in a rational manner. Supporting this prediction, behavioral finance literature consistently indicates that heuristic decision-making is associated with biased information processing (Barberis & Thaler, 2003; Che Hassan et al., 2023; Filbeck et al., 2017; Hirshleifer, 2015; Zahera & Bansal, 2018). The behavioral models of Daniel et al. (1998), Barberis et al. (1998), Gervais and Odean (2001) and Lam et al. (2010, 2012) predict that such biased information processing is caused by overconfidence, representativeness and conservatism, as briefly described by the ensuing paragraphs.

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, apprise their trading ability in a biased manner. They tend to attribute too firmly 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 their ability to generate information and become overconfident about their private information compared to public information. This overconfidence overweighs the private information relative to public information in their subsequent trading decisions. Barber and Odean (2013), Gervais and Odean (2001) and Ishfaq et al. (2020) also show that overconfidence arises with the self-attribution bias, resulting in individuals' failure to learn about their abilities. According to their model, traders who successfully predict the dividend of the next period wrongly believe that the success was due to their superior abilities and, as a result, become overconfident.

Barberis et al. (1998), with their model of investor sentiments, also show that investors are susceptible to conservatism and representativeness biases when updating their beliefs. The conservatism bias indicates that investors retain their prior beliefs and are slow to change them in the face of new evidence. Hence, they may disregard the full information content of public announcements (for example, earnings). Representativeness is an approach to making probability judgments based on the similarity of events. According to Kahneman and Tversky (1972), representativeness is defined as *"the degree to which an event is similar in essential characteristics to its parent population and reflects the salient features of the process by which it is generated."* Investors exposed to representativeness bias are prone to make judgments too quickly based on too small a sample of data. For example, when a company records consistent earnings growth over the past few years, investors may prefer to infer that this past growth pattern is representative of the future earnings growth potential of the company. Consequently, they tend to ignore other information that affects the company's future earnings potential. Extending the work of Barberis et al. (1998), Lam et al. (2010, 2012) also argue that investors are inclined to conservatism and representativeness biases simultaneously due to inappropriate treatment of information when forming their beliefs. According to their behavioral model, heuristics affected by conservatism bias underweight recent observations, whereas those with representativeness bias underweight past observations when making decisions. Supporting these predictions, Wong et al. (2018) empirically prove that individual investors' decisions are affected by representativeness and conservatism biases.

Bias-learning Behavior of Investors and its Association with Investment Experience

Based on the concept of bounded rationality and principles of evolutionary biology, Lo (2004, 2005, 2012) introduced a new perspective called *"Adaptive Market Hypothesis,"* which explains this heuristic decision-making behavior in a dynamic market environment. It shows that when the environment changes, the heuristics used previously may be maladaptive to the new context. However, assuming an evolutionary perspective predicts that heuristics evolve through trial-and-error behavior shaped by the dynamics of the market environment in which this behavior occurs. As further explained by Lo (2004), *"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."* In doing so, they would be able to pursue appropriate heuristics in decision-making. Accordingly, this theory implies that investors learn about biases associated with heuristics from their experiences and, thereby, apply new heuristics for adapting to the market environment.

The effect of investment experience on minimizing biases occurring in investment decisions has been a long-standing puzzle in the behavioral finance literature since the literature reveals both positive and negative effects of investment experience in this phenomenon, as follows. The positive effect is expected based on the belief that investors accumulate knowledge and skills over time and, hence, are less prone to biases as they become more experienced in investing (Dhar & Zhu, 2006; Feng & Seasholes, 2005; List, 2011; Nicolosi et al., 2009). Supporting this prediction, Gervais and Odean (2001), Koestner et al. (2017), and Menkhoff et al. (2013) find that overconfidence bias declines with experience. In addition, Hon-Snir et al. (2012) also discovered that a higher investment experience results in a lower level of representativeness bias. Further, Da Costa Jr et al. (2013), Feng and Seasholes (2005), and Seru et al. (2009) reveal that experienced individual investors are less susceptible to irrational disposition effects as compared to inexperienced investors.

On the contrary, concerning the cognitive aging of investors, it can be argued that individual investors are more inclined to behavioral biases when they grow up and become more experienced since aging weakens their cognitive capacity. The psychological literature reveals that cognitive abilities such as memory and attention decline with age (Salthouse, 2000; Schroeder & Salthouse, 2004), which begins at about the age of 30 (Spaniol & Bayen, 2005). Consequently, information processing could slow down, and mistakes may occur when processing relevant information for decision-making. Hence, even though investors acquire more investment knowledge through their experiences as they grow up, their aging may hinder the effective application of that knowledge in decision-making. Consistent with this view, Korniotis and Kumar (2011) find that older investors possess greater investment knowledge from their experiences. However, they exhibit poor stock selection ability. Accordingly, behavioral biases would tend to increase if the adverse effects of aging dominate the positive effects of the experience. Bhandari and Deaves (2006), Deaves et al. (2010), Glaser and Weber (2007), Kirchler and Maciejovsky (2002), Mishra and Metilda (2015) and Xiao (2015) reveal that the more experienced investors 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 a higher level of overconfidence, representativeness bias, and disposition effect than the inexperienced investors. Further, Gupta and Ahmed (2016) show that psychological biases such as loss aversion, regret aversion, and anchoring are more associated with experienced investors than inexperienced ones.

Addressing this long-standing puzzle on the effect of investment experience on biases occurring in investment decisions, Shantha et al. (2018) propose a model of individual investor learning behavior, providing a comprehensive view of cognitive, affective, social, and behavioral aspects that play a significant role in the learning process. Their model assumes that the investors engage in individual and social learning behaviors. In the case of individual learning, contrary to the reinforcement learning predicted by the Adaptive Market Hypothesis, their model claims that past trading experiences do not merely produce learning effects to minimize behavioral biases. Consistent with the transformative learning theory of Mezirow (1994), it predicts that 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 investment decisions by reflecting upon the associated experiences (Mezirow, 2018). It enables the investors to appropriately revise their biased mental frames to yield more adaptive heuristics for investment decisions. In the event of social learning, based on the insights from the social learning theory of Bandura and Walters (1977) and the practice-based learning model proposed by Nohl (2015), Shantha et al. (2018) predict that copying behaviors of others does not merely produce learning effects since it results to exaggeration of the behavior, delay in incorporating new information into prices and deviation of the behavior significantly from reality (Bossan et al., 2015). They rather predict that investors learn socially when imitated behaviors are inquired upon for knowing about reasons and strategies underlying those behaviors.

METHODOLOGY

Conceptualization

This study adopts the work of Shantha et al. (2018) which claims that investors learn individually through the *"self-reflection"* of past trading experiences rather than the past experiences itself. Accordingly, it predicts that investment experience reduces information processing biases through the mediation effect of self-reflection, as shown by Figure 1 and indicated by hypotheses H1, H2, and H3 below.

Hypothesis 1 (H1): An investor's investment experience (IE) is positively related to the extent of self-reflection (SR) he/she has when learning.

Hypothesis 2 (H2): The level of SR is negatively related to the extent of information processing biases that occur when investing in stocks.

H2a: The level of SR is negatively related to the extent of overconfidence (OC).

H2b: The level of SR is negatively related to the extent of representativeness bias (REP).

H2c: The level of SR is negatively related to the extent of conservatism bias (CON).

Hypothesis 3 (H3): SR mediates the relationship between IE and information processing biases when investing stocks.

H3a: SR mediates the relationship between IE and OC.

H3b: SR mediates the relationship between IE and REP.

H3c: SR mediates the relationship between IE and CON.

In addition to this cognitive aspect of learning, Shantha et. al. (2018) predict that investors' affective states (for example, emotions experienced and attention to mistakes that occurred during past stock trading and interest towards the learning attempt) and relationships with investment advisors and other investors strengthen the individual learning process. Thus, consistent with Shantha et al. (2018), it is hypothesized that investors' desire to learn and have authentic relationships with their investment advisors and other investors moderates the relationship between IE and SR, as shown by hypotheses H4, H5, and H6 below.

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

Hypothesis 5 (H5): An investor's authentic relationship with the investment advisor (ARAD) positively moderates the positive relationship between IE and SR.

Hypothesis 6 (H6): An investor's authentic relationships with other investors (AROT) positively moderate the positive relationship between IE and SR.

Further, as predicted by the social learning theory of Bandura and Walters (1977) and the practice-based learning model proposed by Nohl (2015), investors learn socially by imitating others' behaviors and inquiring them for knowing about reasons and strategies underlying those behaviors. Thus, consistent with Shantha et al. (2018), it is expected that an investor's relationships with other investors facilitate inquiry of information so that he/she is able to learn from others' behaviors to minimize information processing biases. When the relationships with other investors are more trustworthy, the learners will have more confidence in the information received; thus, a higher learning effect would result. Hence, AROT is negatively related to information processing biases occurring when investing in stocks, as indicated by

Hypothesis 7.

Hypothesis 7 (H7): AROT has a negative impact on information processing biases that occur when investing in stocks.

H7a: AROT has a negative impact on OC.

H7b: AROT has a negative impact on REP.

H7c: AROT has a negative impact on CON.

Figure 1 depicts the conceptual model of this study with related hypotheses. As explained with hypotheses H1 to H7, it shows how individual and social learning occurs within individual investors to minimize the biases arising from using heuristics.

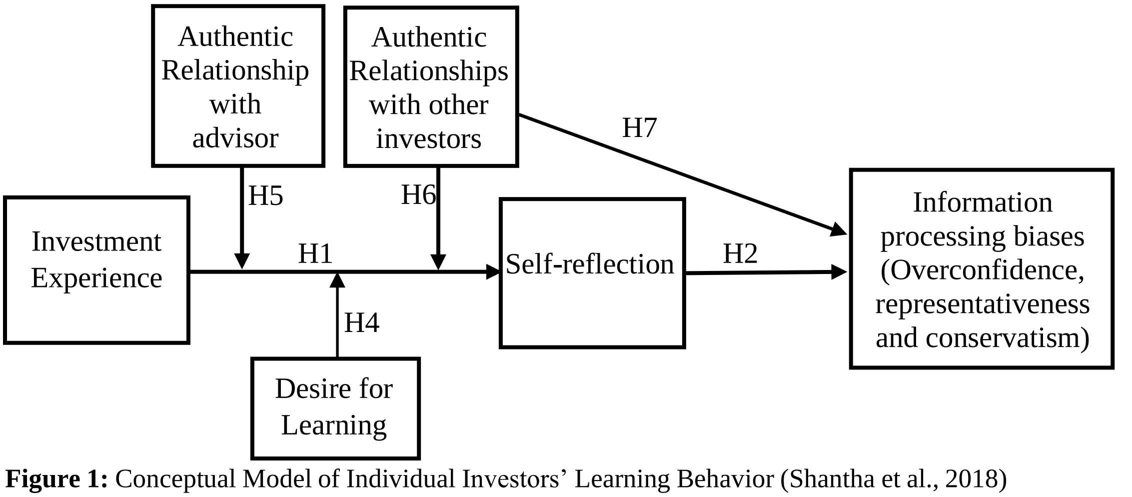

Figure 1: Conceptual Model of Individual Investors' Learning Behavior (Shantha et al., 2018)

Collection of Data

The analysis unit of this study is the individual investors of the CSE who have had active security accounts over the last six months. The data was collected from a web-based questionnaire survey from January to March 2023. 395 valid responses were received to the questionnaire. The responses received appear to be free of non-response bias since the examination of which, based on the procedure suggested by Dooley and Lindner (2003), finds no significant difference between early and late responses.

Questionnaire Design

The questionnaire of the study consisted of two sections. The first section gathered information on the respondents' demographic details and investment characteristics. The second section focused on measuring 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. All the model's constructs 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 the questionnaire were tested in a pilot study with a sample of 30 individual investors. Moreover, the 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 enhance their clarity further. Harman's one-factor test finds that the responses received are free of common method bias.

Measurement of Constructs

The question items used for measuring the constructs, as outlined in Appendix 1, were adopted from the literature, as discussed below. Consistent with the previous behavioral studies, the IE of the respondents was measured in terms of the number of years during which they had been investing in the stock market (Abreu & Mendes, 2012; Mishra & Metilda, 2015; Seru et al., 2009; Yalcin et al., 2016). Adopting the scale proposed by Kember et al. (2000), SR was assessed by three items relating to the process reflection and four items relating to the premise reflection. Concerning information processing biases, relying on the scales developed by Yalcin et al. (2016), OC was measured using four items, while REP and CON were comprised of two items each. Based on the scale proposed by Fisher et al. (2001), the DL construct was measured using these 10 items (Fisher & King, 2010; Williams & Brown, 2013), 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). ARAD and AROT were measured with five items each, adopting the scale used by Kale et al. (2000). However, one item was dropped when measuring ARAD due to low factor loading.

Data Analysis

This study explores how learning occurs within individual investors to minimize their information processing biases. Becker et al. (2013), Evermann and Tate (2016) and Sarstedt et al. (2017) recommend applying 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. Concerning the research setting of this study, the conceptual model consists 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 (Hair et al., 2017; Sarstedt et al., 2017). 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 the 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 and 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. From the participants in 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 males in the Sri Lankan culture. In addition, the proportion of respondents below the age of 35 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

Further, in terms of education level, almost half of the respondents hold a bachelor's degree or higher education qualification. Then, concerning 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 in 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 the trading frequency, only 9.1 percent of the respondents trade stocks daily, while the majority of them trade occasionally. In terms of the attitudes towards risk, nearly 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 evidenced by 19.5 percent holding less than 5 percent of their wealth and 48.6 percent holding 5–15 percent of their 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 the economic crisis, political instability, and COVID-19. With the uncertainty and associated down-market trends, investors may have experienced significant losses in their investment value and, hence, become frustrated and panicked about further losses. Consequently, they tend to behave more risk-averse by shifting their stock investments to safer securities, resulting in a lower stock trading frequency. The mean values of overconfidence, representativeness, and conservatism biases are 3.493, 3.439, and 3.915, respectively. The values greater than 3 indicate that the respondents are prone to these biases 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 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 means an acceptable level of internal consistency reliability of the respective constructs (Gefen et al., 2000; Nunnally & Bernstein, 1994). All the constructs also possess an AVE 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 is 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 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 Information Processing Biases

Figure 2 summarizes the key findings relating to the learning behavior hypothesized in this study. The variance explained (R^2) in SR, OC, REP, and CON constructs are 0.375, 0.095, 0.092, and 0.019, respectively. Q^2 values of SR, OC, and REP constructs are larger than zero, which means an acceptable level of predictive accuracy of these constructs (Sarstedt et al., 2017). Tables 2 to 5 present the estimates of path coefficients, their significance, and f^2 effect sizes to examine the hypotheses relating to individual and social learning behaviors discussed in the following sections.

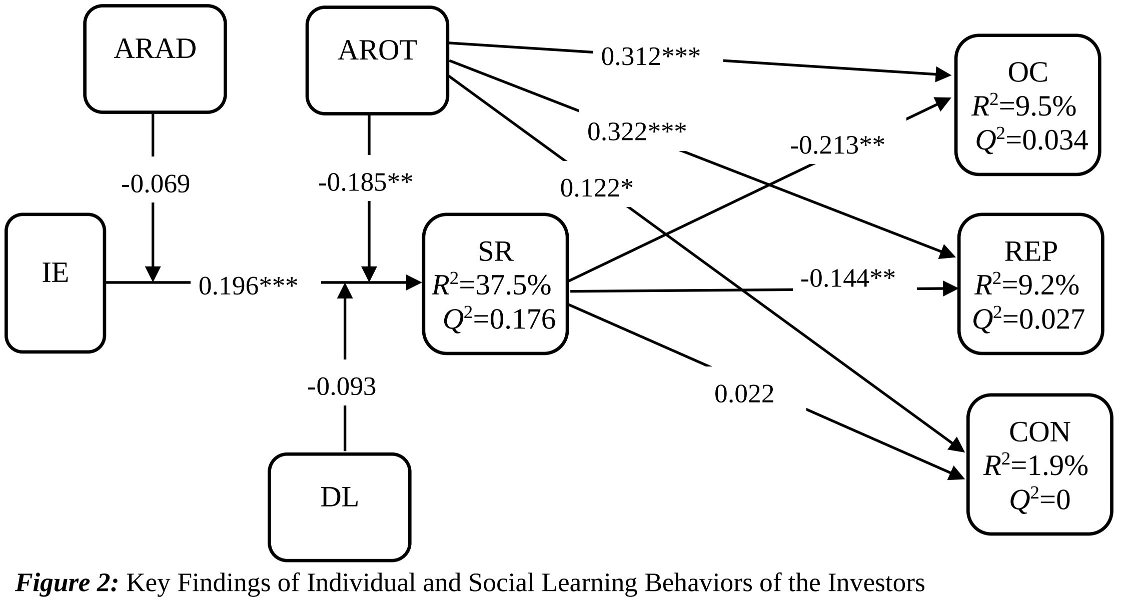

Figure 2: Key Findings of Individual and Social Learning Behaviors of the Investors

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

Individual Learning Behavior

The results, given in Panel A of Table 2, show that IE has a positive impact on SR ($p<0.01$), which, thus, supports the H1 hypothesis. 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 market uncertainties that prevailed during the study period could be considered as a more likely reason for the small effect of IE on SR. As detailed in Section 3.1, investors were frustrated and reduced their stock holding in response to the uncertainties observed during this period. Consequently, they might not have had much interest in self-reflection on their past experiences.

The findings also reveal that SR has a negative impact on OC and REP ($p<0.05$), which confirms the H2a and H2b hypotheses. An increase of one standard deviation unit of SR decreases OC and REP by 0.213 and 0.144 standard deviation units, respectively, which seem to have small effects as reflected by their f^2 values. In addition, consistent with H3a and H3b, SR mediates the relationship between IE and OC ($p<0.10$) and the relationship between IE and REP ($p<0.10$). Table 3 shows the absence of the direct effects of IE on OC and REP. Hence, SR has full mediation effects on these relationships (Zhao et al., 2010). These findings are similar to those of Shantha (2019) on the CSE, which reveals a full mediation effect of self-reflection on the relationship between the experience and herd bias. Conversely, the results do not confirm such effects concerning the CON construct, as given by the H2c and H3c hypotheses. Accordingly, it is evident that not just past investment experiences of the investors but self-reflection upon such experiences reduces their overconfidence and representativeness biases. 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 in a lower level of biases. However, the magnitude of this learning effect appears to be low during the study period due to the investors' lesser tendency to involve in self-reflection, as discussed in the preceding paragraph.

Table 2: Examination of the Hypotheses on Individual Learning Behavior

Hypothesis	Path	Path coefficient	Standard error	*t*-statistic	*p*-value	f^2
Part A: Effect of IE on SR and information processing biases						
H1	IE→SR	0.196	0.069	2.686	0.004***	0.051
H2a	SR→OC	-0.213	0.111	1.953	0.025**	0.047
H2b	SR→REP	-0.144	0.089	1.673	0.048**	0.022
H2c	SR→CON	0.022	0.152	0.270	0.394	0.002
H3a	IE→SR→OC	-0.043	0.027	1.467	0.071*	
H3b	IE→SR→REP	-0.028	0.020	1.386	0.082*	
H3c	IE→SR→CON	0.004	0.031	0.243	0.404	
Part B: Moderating effect of DL on SR						
H4	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	
	DL×IE→SR→REP	0.015	0.021	0.674	0.250	
	DL×IE→SR→CON	-0.001	0.022	0.177	0.430	
Part C: Moderating effect of ARAD on SR						
H5	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	
	ARAD×IE→SR→REP	0.011	0.017	0.624	0.266	
	ARAD×IE→SR→CON	0.001	0.017	0.170	0.433	
Part D: Moderating effect of AROT on SR						
H6	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*	
	AROT×IE→SR→REP	0.025	0.024	1.172	0.121	
	AROT×IE→SR→CON	-0.005	0.031	0.248	0.402	

Note: This table presents the results relating to the individual learning behavior, as hypothesized by H1 through H6. 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 small, medium, and large effects, respectively (Cohen 1988; Sarstedt et al., 2017).

Table 3: Direct Effect of Investment Experience on Information Processing Biases

Path	Path coefficient	Standard error	*t*-statistic	*p*-value
IE→OC	0.141	0.183	0.775	0.219
IE→REP	0.127	0.132	0.961	0.168
IE→CON	0.096	0.110	0.873	0.191

Note: This table reports the estimates relating to the direct association of investment experience with overconfidence, representativeness, and conservatism biases. The results indicate the absence of such direct effects.

Then, concerning the moderating effects, the estimates in part B of Table 2 reveal that DL has no moderating effect on the relationship between IE and SR, as hypothesized by H4. However, Table 4 shows that it has a direct positive impact on SR ($p<0.01$, $f^2=0.162$), which, in turn, has a negative impact on OC ($p<0.05$) and REP ($p<0.10$). 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 individual learning process. According to Panel C of Table 2, ARAD has no positive moderating effects on the relationship between IE and SR. This may be due to the decline in interactions with investment advisors during the study period. As discussed in section 4.1, most of the respondents are characterized by low-risk appetite, low stock holding, and infrequent trading behaviors since they were mostly frustrated and panicked with the down-market trends and the associated losses that occurred during this uncertain period. Consequently, their interactions with investment advisors might become weak, which, in turn, impaired both the amount and confidence of information and guidance that they receive for investing. Hence, the moderating effect of ARAD, as hypothesized by H5, is not evident. Further, contrary to H6, 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 experience and competence in investing, 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.

Table 4: Effect of Desire for Learning in Individual Learning

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**	
DL→SR→REP	-0.060	0.043	1.399	0.081*	
DL→SR→CON	0.007	0.063	0.267	0.395	

Note: This table reports the direct effect of DL on SR and, thereby, on OC, REP, and CON constructs. 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 small, medium, and large effects, respectively (Cohen, 1988; Sarstedt et al., 2017).

Social Learning Behavior

In relation to social learning, hypothesis H7 predicts a negative association between AROT and information processing biases. However, the findings reported in Table 5 do not confirm this hypothesis, which means that the investors' relationships with other investors have not enabled them to learn of their information processing biases during the study period. On the contrary, the findings indicate that an increase in one standard deviation unit of AROT increases OC, REP, and CON by 0.312 ($p<0.01$, $f^2=0.087$), 0.322 ($p<0.01$, $f^2=0.098$) and 0.122 ($p<0.10$, $f^2=0.014$) standard deviation units respectively. Accordingly, the information processing biases appear to have increased through the relationships with other investors, which can be considered an occurrence of *"social conformity behavior"* among individual investors.

Table 5: Examination of the hypotheses on social learning behavior.

Hypothesis	Path	Path coefficient	Standard error	*t*-statistic	*p*-value	f^2
H7a	AROT→OC	0.312	0.062	4.743	0.000***	0.087
H7b	AROT→REP	0.322	0.068	4.583	0.000***	0.098
H7c	AROT→CON	0.122	0.084	1.453	0.073*	0.014

Note: This table presents the results relating to the social learning behavior, as hypothesized by H7. 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 small, medium, and large effects, respectively (Cohen, 1988; Sarstedt et al., 2017).

The social conformity behavior appears when less sophisticated investors merely follow others' trading behaviors for conformity with the behavior of the majority. Lu and Tang (2015) find that peer interactions converge investment behavior to a social norm, where investors who hold stocks less than their peers tend to increase their stock investment, while those who invest in stocks more than their peers trend to decrease their equity allocation. A social conformity behavior could result in representativeness bias as it ignores prior probabilities of the outcome, places more weight on recent information, and is affected by less reliable evidence (Tversky & Kahneman, 1974). As discussed in section 4.1, the majority of the respondents of this study exhibit similar behavioral characteristics such as low risk appetite, infrequent trading and low stock holding. Accordingly, the increased representativeness bias through AROT could be attributed to this social conformity behavior.

The following of others' behaviors also trigger overconfidence bias. Proeger and Meub (2014) find that individuals become overconfident when seeing the conformity of their actions with those of others. In the same way, Lu and Tang (2015) show that, in outcome-based social interaction, investors who have higher equity returns than their peers tend to be overconfident and, consequently, increase their risky investments without concern about the peers' lower return. Accordingly, this social conformity phenomenon can also be considered a possible explanation for the increased overconfidence bias through AROT.

Aggregate Effect of Individual and Social Learning

According to the results discussed in sections 4.3.1 and 4.3.2, investors' self-reflection of past experiences decreases their information processing biases, while the relationships with other investors intensify them. The extent of these effects can be determined by comparing the respective effect sizes as follows. In relation to overconfidence, the effect size of the AROT ($f^2=0.087$) is larger than that of the SR ($f^2=0.047$), which means that the investors exhibit overconfidence in their stock investment decisions. Similarly, they appear to be affected by representativeness bias as its increase from the AROT (f^2*=0.098*) is greater than its decline through the SR behavior (f^2*=0.022*). Conservatism bias also seems to have an impact on stock investment decisions since it is not reduced by SR while increasing through the AROT (f^2*=0.014*). Therefore, it is evident that, despite the presence of the investors' desire for learning to a reasonable degree (f^2*=0.162*), their learning had not adequately taken place during the study period to eliminate information processing biases occurring in stock investment decisions.

CONCLUSIONS AND IMPLICATIONS

This study addresses the issue of how an individual investor could succeed through heuristic decision-making. Based on the implications of the Adaptive Market Hypothesis, Dual-Process Theory, Transformative Learning Theory, Social Learning Theory, and the model of investor learning proposed by Shantha et al. (2018), it attempts to claim that biases associated with irrational heuristics are minimized through individual and social learning behaviors of an individual investor. Based on the findings, it can be concluded that the extent to which the biases get reduced does not merely depend on the level of investment experience that an investor has, but on the extent of self-reflection of the experience that the investor involves when learning. The results also conclude that investors' social conformity behavior increases information processing biases in their decision-making. These findings of the study contribute to the literature and practice as follows.

Contribution to Literature

This study significantly enriches the existing behavioral finance literature on investment behavior and decision-making by offering empirical support for the AMH. The AMH posits that market efficiency evolves as investors adapt to changing market conditions, and this study provides an understanding of the mechanisms underlying such adaptation. Specifically, it demonstrates how heuristic biases in decision-making can be mitigated through individual and social learning. By integrating the AMH with insights from the model of investor learning of Shantha et al. (2018), this study extends the theoretical framework of AMH, showing that learning processes play a crucial role in minimizing biases. In addition, this study challenges the conventional belief that extensive investment experience alone is sufficient to reduce behavioral biases. It introduces the critical concept of self-reflection, revealing that the effectiveness of bias reduction is significantly influenced by how investors reflect on and learn from their experiences. This finding adds a new dimension to understanding the relationship between experience and behavioral biases, suggesting that the quality of self-reflection is as important as the quantity of experience. This perspective provides a more comprehensive view of how experience shapes investor behavior, highlighting the need for reflective learning practices.

Further, even though heuristic decision-making has been extensively studied in the behavioral finance concerning their effects on investment performance and the functioning of financial markets (Che Hassan et al., 2023; Filbeck et al., 2017; Hirshleifer, 2015), studies on mechanisms to minimize the information processing biases associated with heuristics appear to be an unexplored behavioral issue in the literature. (Bílek et al., 2018; Che Hassan et al., 2023). Therefore, this study is the first of its kind, providing empirical evidence on mechanisms for minimizing information processing biases that arise with heuristic decision-making. It suggests a learning approach that should be encouraged among the individual investors to minimize their information processing biases, thereby, the associated possible negative consequences to their wealth. Moreover, it provides an understanding of social influences on investment behavior by distinguishing between social learning and social conformity. Social learning involves actively inquiring about others' behaviors and integrating such information into decision-making, whereas social conformity refers to passively following their behaviors. The findings indicate that social learning is more effective in reducing biases rather than merely conforming to popular trends. This distinction enriches the literature on social influences in finance, offering a more detailed exploration of how different types of social interactions impact investment decision-making.

Contribution to Practice

The findings of the study offer practical insights for individual investors, investment advisors, and stock exchanges. For individual investors, the study highlights the importance of engaging in self-reflection on their investment experiences to identify and learn from biases that have influenced their decisions. This reflective practice enables investors to revise their mental frames, which encompass beliefs, thoughts and assumptions, leading to the adoption of more ecologically rational investment strategies. Continuous self-reflection and learning can enhance investors' sophistication and active participation in the market, ultimately resulting in better investment outcomes. For investment advisors, the findings highlight the necessity of recognizing and addressing the cognitive biases that impede their clients' decision-making processes. Advisors can apply this understanding to develop educational initiatives such as workshops, seminars, and personalized coaching sessions to enhance clients' awareness of their biases and improve their decision-making skills. Advisors can help clients make more informed and rational investment decisions by providing more effective advisory services. Further, the study emphasizes the importance of building strong communication, collaboration, and mutual trust between advisors and clients. Advisors who actively engage with their clients and foster a trusting relationship are more likely to encourage clients to seek advice consistently, regardless of market conditions. This continuous engagement can lead to the development of better investment strategies tailored to adapting to dynamic market conditions. In turn, advisors benefit from increased client retention and loyalty, enhancing their professional reputation and business success. For stock exchanges, the study's insights into investor learning behavior can inform the design of awareness and training programs that promote continuous learning among investors. By organizing educational initiatives such as webinars, online courses, and informational campaigns, stock exchanges can encourage investors to engage in self-reflection and social learning. These programs can help investors to be more ecologically rational in decision-making, which reduces the probability of market phenomena such as bubbles and crashes. By fostering a more informed and rational investor base, stock exchanges can enhance market stability and efficiency, contributing to the overall development of the financial system.

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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	Item Wording	Indicator Loading	Cronbach's Alpha	composite reliability	AVE
Overconfidence (OC)	OC_1	I am an experienced investor	0.707	0.874	0.811	0.532
	OC_2	I feel that on average my investment performs better than the market	0.813			
	OC_3	My past profitable investments were mainly due to my specific investment skills	0.888			
	OC_4	I feel more confident in my own investment opinions over those of friends and colleagues (1 = Strongly disagree, 5 = Strongly agree)	0.423			
Conservatism bias (CON)	CON_1	I rely on previous experience on the market for my next investment	0.749	0.704	0.851	0.744
	CON_2	I try to avoid investing in companies with a history of poor earnings (1 = Strongly disagree, 5 = Strongly agree)	0.963			
Representativeness bias (REP)	REP_1	I forecast the changes in stock prices in the future based on recent stock prices	0.444	0.948	0.704	0.575
	REP_2	I am more concerned on a company's social responsibility when I invest because I believe that a good company will perform well (1 = Strongly disagree, 5 = Strongly agree)	0.976			
Self-reflection (SR)		How would you respond to your past stock investment experiences?		0.867	0.884	0.526
	SR_1	I sometimes question the way others do trading and try to think of a better way.	0.594			
	SR_2	I like to think over what I have been doing and consider alternative ways of doing it.	0.564			
	SR_3	I often evaluate my past stock investment decisions so I can learn from it and improve my next investment.	0.812			
	SR_4	As a result of my investment experience, I have changed the way I make investment decisions.	0.819			
	SR_5	My experience has challenged some of my firmly held ideas and beliefs.	0.638			
	SR_6	As a result of the experience, I have changed the way I invest.	0.816			
	SR_7	I have discovered faults in what I had previously believed to be right. (1 = Strongly disagree, 5 = Strongly agree)	0.781			
Investment Experience (IE)	TradeYrs	How long have you been investing in the stock market? (State in number of years)	1.000	1.000	1.000	1.000
Desire for learning (DL)	DL_1	Please indicate to what extent you feel about the following. I want to learn new information	0.800	0.912	0.928	0.618

Construct	**Indicator Item**	**Item Wording**	**Indicator Loading**	**Cronbach's Alpha**	**composite reliability**	**AVE**
	DL_2	I enjoy learning new information	0.820			
	DL_3	I have a need to learn	0.807			
	DL_4	I enjoy a challenge	0.828			
	DL_5	I do not enjoy studying	---			
	DL_6	I critically evaluate new ideas	0.746			
	DL_7	I learn from my mistakes	0.732			
	DL_8	I need to know why	0.763			
	DL_9	I am open to new ideas	0.787			
	DL_10	When presented with a problem I cannot resolve, I will ask for assistance (R)	---			
		(1 = Strongly disagree, 5 = Strongly agree)				
Authentic relationship with investment advisor (ARAD)		How would you describe your relationship with your investment advisor?		0.874	0.891	0.671
	ARAD_1	I would let my adviser decide everything.	0.869			
	ARAD_2	I prefer to ask my adviser's opinion for investing.	0.775			
	ARAD_3	I would trust my adviser.	0.813			
	ARAD_4	My adviser provides me with information important to make my investment decisions.	---			
	ARAD_5	My adviser cooperates and shares ideas, feelings, beliefs, etc.	0.817			
		(1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Very often, 5 = Always)				
Authentic relationship with other investors (AROT)		How would you describe your relationships with other investors?		0.870	0.887	0.613
	AROT_1	Friendly and can talk about difficulties personally	0.655			
	AROT_2	Mutually trusting	0.791			
	AROT_3	Mutually respectful	0.832			
	AROT_4	Highly give-and-take	0.779			
	AROT_5	Share ideas, feelings, beliefs, etc.	0.842			
		(1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Very often, 5 = Always)				

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	CON	DL	OC	REP	SR	IE	Is discriminant validity met?
ARAD	**0.819**								Yes
AROT	0.428	**0.783**							Yes
CON	0.054	0.134	**0.863**						Yes
DL	0.421	0.532	0.049	**0.786**					Yes
OC	-0.010	0.229	0.478	0.065	**0.730**				Yes
REP	0.088	0.267	0.567	0.012	0.462	**0.758**			Yes
SR	0.333	0.306	0.078	0.543	-0.126	-0.053	**0.726**		Yes
IE	0.101	0.171	0.079	0.185	-0.029	0.128	0.208	Single item	Yes

Note: This table presents a comparison between each construct's 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).

Heterotrait-Monotrait (HTMT) Criterion Analysis for Assessing Discriminant Validity

	ARAD	AROT	CON	DL	OC	REP	SR	IE
ARAD								
AROT	0.463							
CON	0.153	0.186						
DL	0.456	0.589	0.090					
OC	0.208	0.235	0.721	0.156				
REP	0.218	0.401	1.142	0.163	0.830			
SR	0.353	0.324	0.182	0.597	0.182	0.229		
IE	0.117	0.172	0.070	0.193	0.079	0.178	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	
CON		1.103			1.103
OC		1.103			1.103
REP		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 raw wise) for the assessment of multicollinearity. The VIF value of 5 or above indicates collinearity issues (Cassel et al., 1999; Hair, Ringle et al., 2011).