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Individual Investors' Learning Behavior and Its Impact on Their Herd Bias: An Integrated Analysis in the Context of Stock Trading

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Abstract: The efficient functioning of capital markets ensures that information on companies' sustainable development endeavors is fully and instantly incorporated into stock prices, which facilitates them in raising capital requirements at a lower cost. It, however, is impaired when market participants are inclined to behavioral biases. The Adaptive Market Hypothesis predicts that such behavioral biases are evolutionary. In that sense, market participants are capable of learning their behavioral mistakes and adapting to market conditions over time. Based on this perspective, this paper aims to explore how learning occurs within individual investors to reduce their herd bias. The data was collected by distributing a web-based self-administrated questionnaire to a sample of 1000 individual investors of the Colombo Stock Exchange, who were randomly selected during a period from March to August 2018. A total of 189 responses were received, which were analyzed using the structural equation modelling technique to test the hypotheses of the theoretical model. The results show that learning takes place when investors cognitively evaluate past trading experiences, which is induced by their desire for learning, and, consequently, reduces their herd bias. However, as the model predicts, strengthening this cognitive reflection from the relationship with the investment advisor and social learning among investors through their peer-relationships appear to be absent due to uncertain market conditions prevailed during the study period and dominance of unsophisticated investors in the market. From these findings, this paper concludes that the cognitive reflection of past experiences and the nature of the trading environment determine the extent of learning within individual investors.

Keywords: herding; behavioral bias; adaptive market hypothesis; self-reflection; Colombo stock exchange; market efficiency; investor education

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"Do not be embarrassed by your failures, learn from them and start again."

Richard Branson

1. Introduction

The concept of sustainable development has now become an integral aspect of a company's strategic planning process. Therefore, it has become a guiding principle when formulating business policies and strategies in striving to achieve its objectives. As stated in Brundtland [1], "sustainable development implies meeting the needs of the present without compromising the ability of future generations to meet their own needs." When concerning the financing side, capital markets should promote sustainable development by facilitating companies to raise capital at a lower cost to finance their endeavor to become sustainable. However, Waygood [2] highlights that this role is currently impaired due to inefficiencies of capital markets which, from the sustainable development viewpoint, indicate the inability of the markets to recognize and reward companies' right conducts to become sustainable. As a result, the information on companies' sustainable development endeavor is not fully and instantly incorporated into prices of their stocks. Waygood [2] further emphasizes that the failure of the investors' predictive power is the main reason of market inefficiency.

The behavioral finance literature shows that individual investors are less sophisticated than institutional investors, primarily due to their limited attention, memory, time, education, and processing capabilities. As a consequence, they are more likely to use simple heuristics or rules of thumb in their decision making, which would become maladaptive in a dynamic market environment [3–5]. The literature suggests that such maladaptive heuristics indicate irrationality of investors, which is classified as behavioral biases or mistakes in their decision-making [6]. These behavioral biases could give rise to deviation of prices of securities from their fundamental values, which results in inefficiencies in financial markets. Accordingly, investor sophistication plays a significant role in efficient functioning of a capital market so that capital is allocated to companies' sustainable developments at a lower cost, which enhances their long-term shareholder value.

One of behavioral biases extensively discussed in the literature is herding. It is one's propensity to abandon information and belief, and infer them from the actions of others in making choices. Despite the evidence on herd bias under different market states and characteristics, and consequences such as market bubbles, crashes, and increased volatility, it is interesting to note that certain previous studies reveal its declining tendency over time [7,8]. This implies a movement towards the market efficiency status. However, to the best of my knowledge, there is no study in the literature providing empirical evidence on the factors that ground for the diminishing herd behavior in a financial market. Accordingly, this paper intends to fill this gap in the literature by studying a case of a stock market where herd bias appears to decrease over time.

Given the research gap this work addresses, the Colombo Stock Exchange (CSE) of Sri Lanka, a frontier stock market, appears to be an ideal case to study due to the following reasons. First, when compared to developed and emerging markets, frontier markets are more vulnerable for herding due to higher uncertainty in an informational and trading environment [9]. Second, political uncertainty and economic crisis of the country during the past few years, and weaknesses in the regulatory structure of the CSE would have further intensified the market uncertainties, stimulating investors to herd when trading stocks. Third, the CSE exhibits strong herd bias during the 2000–2012 period, which, tends to decline and disappears afterwards [8,10].

The effectiveness in regulatory reforms and investor learning behavior are the two possible reasons suggested in the literature for the decline in herd behavior [7,8]. The CSE, however, has not undergone significant regulatory reforms during the period over which the anti-herding occurred. Therefore, this study aims to explore how learning occurs within individual investors to minimize their herd bias. The data was collected through a web-based self-administrated questionnaire distributed to a sample of 1000 individual investors randomly selected during the period of March to August 2018. The responses received, totaling 189, were analyzed using the structural equation modelling technique to test the hypotheses. Supporting the herding literature, the results reveal that, in the presence of uncertain market conditions, herd bias tends to exaggerate among investors through the effect of their peer-relationships. Conversely, it is also evident that they incline to learn the irrationality of herding by reflecting on their past experiences. Hence, they shift away from such irrational behavior when trading stocks. As a consequence, consistent with the previous studies on the CSE, herd bias appears to decline at the aggregate market level since the magnitude of the investors' learning is large enough to outweigh the increased herd bias through their peer-relationships.

This study provides the following five contributions to the academia and industry. First, according to the herding literature, an examination of investors' learning behavior by integrating its impact on their behavioral biases has not been conducted in a single study at the individual unit of analysis. Hence, this is the first of its kind of studies providing empirical evidence on how learning arises within individual investors to reduce their herd tendency occurring when trading stocks. The findings of this study can be adopted when designing training programs for individual investors to improve their sophistication for lowering behavioral biases in decision-making. Second, this study is the first to apply the model of investor learning behavior proposed by Shantha et al. [11], which facilitates the examination of the learning behavior of the individual investors based on the data collected in a real market setting. Third, it attempts to extend the works of Shantha [8] and Xiaofang and Shantha [10] by exploring the factors that account for the declining herd behavior in the CSE. Fourth, the empirical results are derived from primary data sources, which is limitedly available in the behavioral finance literature [6]. Fifth, this study is conducted on a frontier stock market, which is a category of financial markets that, on one hand, is an ideal ground for the examination of herding and, on the other hand, has not had much focus in the existing herding studies so far [9,12].

The reminder of the paper is organized as follows. Section 2 elaborates how investor sophistication relates to the sustainable development of companies and provides a review of the relevant literature on herding and learning behaviors of investors. Section 3 discusses the nature of trading and informational environment of the CSE, which would have stimulated herd behavior in the market. Section 4 introduces the conceptual model and hypotheses. The research design and methodology used in this work are presented in Section 5. Section 6 shows the results related to the assessment of the reliability and validity of the model's constructs, while Section 7 provides the empirical test of the hypotheses to infer about the nature and extent of learning and its effect on herd bias. Section 8 concludes the paper with its implications to practice. The limitations of this study and the avenues for future research are discussed in Section 9.

2. Literature Review

2.1. Investor Sophistication and Sustainable Development

The capital market is important to a country since it provides finance for the economic development. It mobilizes savings of surplus units into medium to long-term investments in the forms of financial assets such as equity shares and corporate bonds, and thereby, enables companies to raise capital to finance their development projects. However, the cost of capital limits the amount of finance that can be raised for developments. In other words, a higher cost of capital would reduce the extent of activities that a company could undertake for its sustainable development. Hence, the sustainable development would be enhanced if the capital required for such long-term development plans could be raised at a lower cost.

The cost of capital is the average cost of financial assets that a company sources to obtain its long-term capital. Most of such financial assets, if not all, are traded on the capital market. Investors allot their funds by buying and selling of them, which ultimately affect the cost of the capital of the issuing companies. Hence, a capital market should facilitate investors to recognize the sustainability of development efforts of companies and allot funds efficiently so that the companies can raise capital at a lower cost. For this purpose, the markets should be allocationally efficient. The allocational efficiency arises when relevant information to judge risk-return and sustainability of development projects is readily available to investors to make their decisions. However, the information availability does not merely guarantee that investors recognize a sustainable endeavor and produce efficient allocation of their funds. Rather, the investors should possess the capacity to use such information to make accurate decisions. Accordingly, the investor sophistication plays a vital role in the efficient functioning of capital markets so that capital could be raised for sustainable developments at a lower cost [2].

2.2. Previous Studies on Herd Behavior

Herd behavior is one of the behavioral biases that has been extensively investigated in behavioral finance over the past few decades. The literature reveals the nature of herding, reasons underlying its occurrence, and its consequences for the functioning of markets [9,13–15]. The previous studies also find that herding is prevalent among different investor-types (for example, retail and institutional investors) and likely to exaggerate through different market states and characteristics (for example, up vs. down market movement days, periods of high vs. low volatility, high vs. low trading volume days, cross-country effects, and effect of macro-economic factors). These studies are mostly conducted with respect to developed and emerging stock markets. However, compared to the developed and emerging markets, the frontier markets are weaker in terms of lower transparency, lower liquidity, higher information asymmetry, dominance of noise trading, and higher volatility. As a result, herding can be expected to be more prominent in frontier markets [9,12,16]. Thus, greater attention has focused on the study of herd phenomenon in frontier stock exchanges.

The evolutionary nature of behavioral biases is another line of research presently being considered in the behavioral finance. It emerged with the Adaptive Market Hypothesis (AMH) proposed by Lo [3–5], a theoretical framework which predicts an evolving efficiency of financial markets. According to the AMH, market participants' behavior is evolutionary over time and in response to market dynamics, and this evolutionary process enables them to learn their biased behaviors for adapting to market conditions. Hence, it can be expected that biases tend to decline and, as a result, the market may approach its efficiency status through their mistake-learning process. Supporting this prediction, Ito et al. [17] find that investors' learning behavior is an underlying factor for the evolving efficiency of financial markets.

The literature provides evidence for the evolving nature of herd behavior in financial markets. Choe et al. [18] and Hwang and Salmon [19] find a tendency to decrease herd bias after crisis periods. In the context of emerging markets, the study of Yao, Ma, and He [7] shows that herd behavior diminishes over time in the Chinese Stock Markets. Furthermore, relating to frontier stock markets, Nguyen [20] finds strong evidence of herding during the 2009–2016 period, whereas no evidence of this behavior afterwards was present in the stock market of Vietnam. Both Nguyen [20] and Yao, Ma and He [7] suggest the effectiveness of regulatory reforms in the respective markets as a possible reason for the decline in herd bias. Similar results have been reported with respect to the CSE of Sri Lanka. Shantha [8] and Xiaofang and Shantha [10] reveal a strong tendency to herd from 2000–2009 (a period of political uncertainty due to civil war) and 2009–2012 (market bubble and crash periods), and the evidence on anti-herding behavior after the market crash. Since there has not been significant regulatory reforms during this anti-herding period, Shantha [8] suggests that investors may have learned the irrationality of herding from the financial losses experienced during the period of the market crash, which reduced their herd tendency. The current study attempts to extend the work of Shantha [8] by exploring how the investors' learning has been effected to lower and/or disappear herd behavior in the CSE.

2.3. Previous Studies on Learning Behavior

The study of investors' learning has mostly been carried out in artificial market environments using agent-based financial models, postulating two approaches of learning that an investor engages in: individual learning and social learning [21–28]. The former represents an investor's attempt to learn by his/her own, whereas, in the latter case, the learning occurs by imitating the others' behaviors. Yamamoto [22] finds that wealthy investors involved in individual learning while other investors follow social learning by imitating the actions of the wealthy investors. Yamamoto [22] and Bossan, Jann and Hammerstein [27] show that social learning efforts are widespread among individual investors as a consequence of an uncertain informational environment and/or high cost of individual learning. Bossan, Jann and Hammerstein [27], by examining different social learning procedures, find that payoff-biased and imitating the wealthiest yield superior outcomes than individual learning.

When modeling the individual form of learning, the agent-based models typically assume the reinforcement learning (RL) since investors' heuristic biases would result in trial-and-error behaviors for adapting to dynamic market conditions. However, Pastore, Esposito, and Vasilaki [28] find that only a subset of players in their study sample follow the RL, which is insufficient to confirm the RL as a component of investors' trading decisions. Furthermore, if the RL assumption holds true, a higher stock trading experience would result in better investment strategies. However, the previous studies provide mix evidence related to this prediction since, despite the evidence supporting this RL [29–37], certain studies show some contradictory evidence as follows. Chevalier and Ellison [38] find a negative relationship between the investment experience and performance. In addition, Agarwal et al. [39] reveal that the relationship between investment experience and performance takes a reverse U shape form, which represents the fact that investment performance tends to decline when the experience increases beyond a particular level. Bhandari and Deaves [40], Xiao [41], Bodnaruk and Simonov [42], Wulfmeyer [43], and Chang [44] also find that the experience escalates overconfidence and disposition effect, which results in a lower investment performance. On the other hand, when social learning is concerned, the herding literature reveals that imitating others' behaviors is an irrationality, which, in the event of becoming a market-wide trend, causes unfavorable effects to a financial market such as increased volatility, speculative bubbles, and crashes [6,15]. In addition to the way learning is assumed, the agent-based models provide a weak representation of investor behavior due to unrealistic parameter configurations adopted for formulating the models such as assumptions on the number of assets traded, number of agents, timing of decisions, information and execution of trade, and speed at which agents update their behavioral rules [24,45]. Furthermore, a large number of such parameter configurations poses difficulties in modeling learning processes, which affects the reasonableness of evidence generated by these models [46]. Hence, in view of these findings, the existing agent-based studies do not appear to deliver a fair representation of an investor's learning behavior occurred in a real stock market.

3. Regulatory and Trading Environment of the CSE

The CSE was established in 1985 as a company limited by guarantee under the Companies Act No. 17 of 1982 and mutually owned by 15 stockbrokers. It provides a trading platform for both debt and equity instruments and has 297 listed companies, representing 20 business sectors with a market capitalization of LKR 2839.45 billion as of 31 December, 2018, which corresponds to about 20 percent of the GDP of the country. A majority of stock trading is executed by local investors, which is approximately 85% of the total number of stock traded and 96% of the total number of trades. In terms of investor-types, retail investors currently dominate the market, accounting for more than 90% of the total market capitalization.

In 1987, the Securities Council Act No. 36 of 1987 was enacted, which established the regulator, the Securities and Exchange Commission (SEC) of Sri Lanka, to facilitate orderly and fair functioning of the capital market. The act was amended in 1991, 2003, and 2009 to strengthen the aspects related to regulation and supervision. However, during the last decade, weaknesses in the current regulatory structure are apparent with the market bubble, a crash that occurred over the 2009–2012 period, and certain instances of insider trading and price manipulations, which resulted in unfavorable consequences such as information asymmetry, low transparency, high volatility, and a few number of securities actively traded in the market. Particularly, over the past few years, political and economic crises of the country prompted an uncertain trading environment, causing impediments to the investor participation and trading activities of the CSE. Consequently, the market experienced a declining trend, as reflected by its All Share Price Index which, recorded at 7605.79 on the first day of the new government in 2015, dropped to 6052.37 as of 31 December, 2018, which is a decline of 20% during this four-year period.

This uncertain informational and trading environment of the CSE may motivate investors to suppress their own information and imitate others' behaviors for information when making their trading decisions [47]. On the other hand, consistent with the implications of Lo [4,5] and Shantha [8], such irrational behaviors of investors could decline when they learn based on their past experiences, which is further stimulated through the educational initiatives of the CSE. The awareness campaigns and investor education programs for investing in the stock market are regularly conducted by the CSE in association with the SEC to enhance their financial literacy and stock market participation.

In 2016, it launched an online educational portal to offer learning material, training and analyses, which added a new dimension to the investor education initiatives. Thus, it can be expected that the investors, in light of these educational initiatives and their trading experiences, would be able to learn their mistakes such as herding and shift away from such irrational behaviors when making decisions to buy/sell stock.

4. Conceptual Model and Hypotheses

The conceptual model used in this paper is based on the work of Shantha, Xiaofang, and Gamini [11], which, incorporating ideas from the behavioral finance and learning literature, proposes a behavioral model to examine investor learning behavior in the context of stock trading. Similar to the learning behavior modeled through agent-based models, their model assumes that investors exhibit individual learning and/or social learning for adapting their investment behavior to dynamic market conditions. However, this model is different from the existing agent-based models in terms of the following features. Unlike the agent-based models that configure only the parameters related to learning behavior of investors, the new behavioral model can be used to study the learning behavior by integrating its effects on their behavioral biases or frame of reference on investing. Furthermore, based on the learning literature, it conceptualizes learning holistically by incorporating cognitive, affective, and social aspects of learning as well as the behavioral aspects typically concerned in the existing agent-based models. The extent of individual and social learning conceptualized in this model can also be empirically measured using primary data obtained in a real market setting.

The model, as shown in Figure 1, assumes that the individual learning occurs within an investor when he/she cognitively evaluates past trading experiences. Accordingly, this cognitive evaluation of experiences, known as "self-reflection," is the mechanism of the individual form of learning, which, in turn, reduces herd bias, as given by the following hypotheses.

Hypothesis 1 (H1). *An investor's trading experience (TE) 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 herd bias (HERD) that occurred when trading stocks.*

Hypothesis 3 (H3). *SR mediates the relationship between TE and HERD that occurred when trading stocks.*

In addition, the model predicts that an investor's authentic relationships with the investment advisor and other investors strengthen the individual learning process. Consistent with Shantha, Xiaofang, and Gamini [11], these social relationships allow investors to obtain relevant information and practical knowledge to learn their mistakes. In particular, with more authentic relationships and with higher trustworthiness relationships, they feel a higher confidence regarding the information and knowledge obtained. Thus, the effect is greater in such relationships in their individual learning process. Hence, an investor's authentic relationships with the investment advisor and other investors are expected to positively moderate the relationship between the trading experience and self-reflection, as hypothesized below.

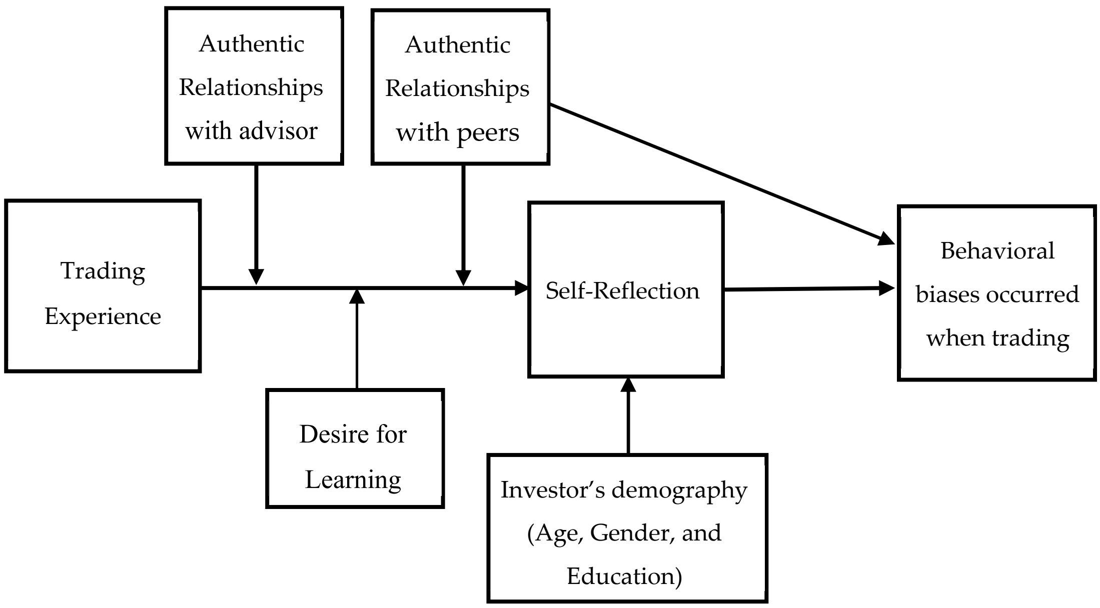

Figure 1. Conceptual framework of investor learning behavior. (Adopted from Shantha et al. [11]).

Hypothesis 4 (H4). *An investor's authentic relationship with the investment advisor (ARAD) positively moderates the positive relationship between TE and SR.*

Hypothesis 5 (H5). *An investor's authentic relationships with other investors (AROT) positively moderate the positive relationship between TE and SR.*

The model also assumes that an investor's desire for learning strengthens the individual learning process. The desire for learning represents the affective aspects such as interest, attention, emotions, and frustrations that influence the cognitive functioning of the brain when learning. Shantha, Xiaofang, and Gamini [11] show that these affects improve the creativity, motivation, and efficiency of learning, which strengthen the self-reflection of experiences. Accordingly, the desire for learning is expected to have a positive moderating effect on the relationship between the trading experience and self-reflection, as hypothesized below.

Hypothesis 6 (H6). *An investor's desire for learning (DL) positively moderates the positive relationship between TE and SR.*

Consistent with the behavioral finance and learning literature, the model argues that merely imitating others' behaviors does not produce the social form of learning. Rather it takes place when the information on strategies underlying those imitated behaviors are known to the learner [11]. Accordingly, the model predicts that the authentic relationships with other investors enable inquiry of such information in the social learning process, which means they are negatively related to herd bias occurring when trading stocks, as reflected by Hypothesis 7.

Hypothesis 7 (H7). *AROT have a negative impact on HERD that occurred when trading stocks.*

The investors' age, gender, and education level are incorporated in the conceptual framework as potential control variables of self-reflection. As argued by Shantha, Xiaofang, and Gamini [11] in their model of investor learning behavior, an investor's ability to be self-reflective is an outcome of his/her "mature cognitive development." Thus, these socio-demographic factors would influence the self-reflection process, as described below. The older investors are more likely to possess a higher trading experience than younger ones, and become more self-reflective. Furthermore, men may be more interested in stock trading than women, which means, as a result, they gain a higher experience and show a greater reflective capacity. Similarly, the level of education would be positively related to the experience and self-reflection. Hence, it is important to incorporate these relationships to avoid alternative explanations and show the unique relationship between the trading experience and self-reflection. Accordingly, the model assumes that the Hypotheses 1, 4, 5, and 6 hold when controlling for the investor's age, gender, and education level.

However, the examination of the association of these socio-demographic variables with trading experience and self-reflection constructs reveals that these variables are not really confounders to be controlled in the analysis [48]. As shown in Tables 7 and 8, the age and gender are not significantly associated with the self-reflection. Even though education is associated with self-reflection, it is not related to trading experience, which is not only statistically based on the results of the one-way ANOVA test, but also in the manner it is measured in the study. Accordingly, consistent with the guidelines provided by Bernerth and Aguinis [49], these potential control variables are excluded from the analysis. Consequently, the hypotheses are examined without controlling for age, gender, and education level. The results are discussed as to whether the level of self-reflection varies with respect to these socio-demographic variables, as given by Hypothesis 8.

Hypothesis 8 (H8). *There are significant differences in investors' SR level between male and female, among different age categories and education levels.*

5. Research Design

5.1. Data Collection

The individual investors who are involved in trading stocks in the CSE is the unit of analysis of this study. A web-based questionnaire survey was conducted for data collection by emailing the online link of the questionnaire to investors whose security accounts have been active over the last six months. This method has advantages of having lower interviewer-bias since the participants can use their discretion when responding to the questionnaire, and is less susceptible to social desirability bias [50]. During the data collection process, conducted from March to August 2018, a total of 1000 investors randomly selected are invited to answer the questionnaire. The responses received were 189, which represents a response rate of 19%. As discussed in Section 3, the unfavorable market conditions prevailed during the period of the study could be attributed to this low response rate. The non-response bias, examined following the procedure proposed by Dooley and Lindner [51], was not found to exist in the responses received.

5.2. Characteristics of the Sample

The analysis of the demography and the investment profile of the survey participants are given in Appendix B. It shows that 71.4 percent of the respondents are male. In terms of age, about 40 percent of the respondents are below 35 years of age, while 44 percent falls in the age category of 35–54 years. Furthermore, about half of the respondents possess a bachelor's degree or higher education. The sample also includes a combination of private sector (78.3 percent) and public sector (4.8 percent) employees, retired (5.8 percent), self-employed (8.5 percent), and unemployed (2.6 percent) individuals. Hence, the sample appears to represent fairly the demographic characteristics of the individual investor population in the CSE. With respect to the respondents' trading experience which is, on average, 11 years (SD = 6.18), the sample includes 4.8 percent of investors possessing 2 years or less experience while 11.1 percent have 18 years or more of experience. Thus, it seems that data has been collected from a balanced combination of high experienced and low experienced investors. In terms of the trading frequency, 59.3 percent of the respondents trade stocks occasionally while only 9.5 percent of them are involved in daily trading. The percentage of respondents having a low risk appetite (46.6 percent) is far greater than those with a high risk appetite (30.6 percent). As a consequence, their tendency to invest in stocks is rather low, as 20.1 percent and 48.1 percent hold, respectively, less than 5 percent and 5–15 percent of wealth in stock. Accordingly, most respondents exhibit a low risk appetite, a low trading frequency, and low stock investments, which could be attributed to the uncertain market conditions prevailed in the CSE during the study period. The uncertainty may have caused investors to become more risk-averse, which results in a shift of their investments to safer securities. This, in turn, reduces their trading frequency.

5.3. Questionnaire Design

The questionnaire consisted of a total of 14 question items, including the items related to socioeconomic characteristics such as age, gender, marital status, education and occupation, and investment profile such as trading frequency, risk appetite, and stock investment of the individual investors. When designing the questionnaire, the following procedure, as suggested by Podsakoff et al. [52], was applied to reduce the common method bias. All scales used to measure the constructs of the conceptual model were adapted from the literature and modified their wording appropriately to suit the study, as shown in Appendix A. The measurement scale of each construct was presented in a separate section of the questionnaire with different sets of instructions to reduce respondents' anxiety. The respondents were also informed that there was no right or wrong answers and their responses were kept anonymous. In addition, the questionnaire was pre-tested before the survey in a sample of 30 individual investors in an attempt to enhance its face and content validity. Furthermore, the meaning and wording of the measurement items were discussed with three academics and three investment advisors to further ensure the clarity of the questions asked and instructions provided to answer the questionnaire. Moreover, Harman's one-factor test reveals that the common method bias is absent in data.

5.4. Measurement Scales

Appendix A provides an overview of the measurement scales used to measure the constructs of the conceptual model. Consistent with the studies of Abreu and Mendes [53] and Mishra and Metilda [54], the trading experience was measured by asking the participants to mention the number of years over which they had been trading stocks on the CSE. The work of Kember et al. [55] was used to measure the extent to which the investors exercise their self-reflection for learning. Of the three levels of reflection manifested in their scale, this study adapted the items relating to the process and premise reflection levels. The process reflection refers to how a person perceives, thinks, feels, and acts in response to his/her past experiences, whereas the premise reflection, the deepest level of reflection, results in identifying psychological and cultural limitations in one's established frame of reference [56]. Accordingly, the self-reflection was measured by seven items, consisting of three items associated with the process reflection and four items related to the premise reflection. The extent of the survey participants inclined to herd bias was assessed following the studies of Waweru et al. [57] and Kengatharan and Kengatharan [58]. Waweru, Munyoki, and Uliana [57] found that investors tend to trade around stock's price changes, popularity, and past trends, which result in herd behavior among investors. Kengatharan and Kengatharan [58] used these behavioral factors in their scale to measure herd bias of the individual investors of the CSE. Consistent with these works, three items, representing these three behavioral characteristics, were used to measure herd bias of the respondents.

Relating to the moderating variables, the following measurement scales were adapted. The assessment of the participants' desire for learning was based on the self-directed learning readiness scale proposed by Fisher et al. [59]. Their scale originally included 12 items to measure the desire for learning. However, the findings of Fisher and King [60] and Williams and Brown [61] confirmed for a 10-item scale that showed a better model fit when compared to the original 12-item scale. Of these 10 items, this study adapted only eight items since two items were dropped due to low factor loading, as indicated by loading relevant test [62]. Authentic relationships with the investment advisor and other investors were each measured by a five-item scale based on the work of Kale et al. [63]. However, one item was removed when measuring an authentic relationship with the investment advisor due to low factor loading.

5.5. Methodology

The conceptual model, discussed in Section 4, intends to predict the determinants of investors' learning behavior and explain their effects on herd bias. The literature, for example, Becker et al. [64], Evermann and Tate [65], and Sarstedt et al. [66] suggest to use the Partial Least Squares Structural Equation Modeling (PLS-SEM) when the goal of the analysis is to predict and explain a target construct and identify its predecessors. Accordingly, the data analysis was conducted using the PLS-SEM, supported by SmartPLS 3 software. When compared with the factor-based SEM, the PLS-SEM has advantages such as higher statistical power, which is appropriate in the case of exploratory research, ability to handle complex models with many constructs and indicator variables, consistent estimates of parameters, and flexibility in terms of sample size and parametric distributional assumptions such as multivariate normality (Sarstedt, Ringle and Hair [66], Hair, et al. [67], and references therein).

Consistent with the procedure suggested by Sarstedt et al. [68], the following two steps were taken in the data analysis process. First, the measurement model was evaluated to ensure the measurement quality of the model's constructs. After that, the structural model was evaluated for its predictive capability and testing the hypothesized relationships. Since the constructs were reflectively specified, their measurement quality was evaluated in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. In the second step, when evaluating the structural model, the model was checked for collinearity issues by analyzing the variance inflation factor (VIF). Afterward, the model's predictive capability, as reflected by the coefficient of determination (R^2), cross-validated redundancy (Q^2), and effect-size (f^2), was assessed and the hypotheses were examined to infer the determinants of the learning behavior and their effects on herd bias. The model's predictive accuracy, as indicated by Q^2, was estimated based on the blindfolding procedure with an omission distance of six [69–71]. f^2, a measure of the effect-size of a particular predictor variable on its endogenous variable, was calculated by following the procedure suggested by Henseler and Chin [72]. The significance of path coefficients for hypothesis testing was estimated using 5000 bootstrap subsamples at the significance level of 5 percent [67].

6. Reliability and Validity of Measurements

The results related to the assessment of the reliability and validity of the constructs are provided in Tables 1–3, and Appendix C. After performing the loading relevant test [62], indicator items demonstrate a satisfactory level of their reliability since, except for a few indicators, all other indicators show loading values greater than 0.7 on their respective constructs, as given in Table 1 [73]. In addition, Cronbach's Alpha and Composite Reliability values of all the constructs exceed the 0.7 level, which indicates their internal consistency reliability [74,75]. Furthermore, all the constructs exhibit an average variance extracted value (AVE) in excess of the cut-off level of 0.5 for their convergent validity. The discriminant validity was assessed by referring to Fornell and Larcker criterion, cross loadings, and Heterotrait-monotrait (HTMT) criterion, as follows. Table 2 shows that the square root of AVE values of all the constructs are higher than their correlation coefficients with other constructs [76]. As given in Appendix C, each indicator loads at the highest value to the construct to which it relates [77,78]. The HTMT ratio of correlations, provided in Table 3, are less than the 0.85 level [79]. Hence, these results provide strong evidence of discriminant validity of the model's constructs. Moreover, the VIF values, which are shown in Table 4, do not indicate a multi-collinearity issue in the model since they are less than five [80,81].

Table 1. Assessment of the measurement quality of the model's constructs.

Construct	Indicator Item	Indicator Loading	Cronbach's Alpha	CR	AVE
ARAD	Arad_1	0.866	0.875	0.891	0.671
	Arad_2	0.777			
	Arad_3	0.811			
	Arad_5	0.820			
AROT	Arot_1	0.628	0.851	0.890	0.622
	Arot_2	0.842			
	Arot_3	0.838			
	Arot_4	0.819			
	Arot_5	0.794			
DL	Dl_1	0.799	0.912	0.928	0.618
	Dl_2	0.819			
	Dl_3	0.806			
	Dl_4	0.827			
	Dl_6	0.748			
	Dl_7	0.733			
	Dl_8	0.763			
	Dl_9	0.788			
HERD	Herd_1	0.875	0.836	0.891	0.732
	Herd_2	0.861			
	Herd_3	0.830			
SR	Sr_1	0.567	0.879	0.883	0.527
	Sr_2	0.535			
	Sr_3	0.819			
	Sr_4	0.838			
	Sr_5	0.649			
	Sr_6	0.815			
	Sr_7	0.789			
TE	TradeYrs	1.000	1.000	1.000	1.000

Note: This table presents indicator items' loading, cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) values for assessing the measurement quality of the model's constructs. An indicator loading value greater than 0.5 shows the indicator reliability [73]. A set of indicators to measure each construct is found from the loading relevant test [62]. The Cronbach's alpha and CR values greater than 0.7 indicate the internal consistency reliability [74,75]. The AVE value greater than 0.5 represents the convergent validity [76,82].

Table 2. Fornell-Larcker criterion analysis for assessing discriminant validity.

	ARAD	AROT	DL	HERD	SR	TE	Discriminant Validity Met?
ARAD	**0.819**						Yes
AROT	0.415	**0.788**					Yes
DL	0.421	0.523	**0.786**				Yes
HERD	−0.099	0.145	−0.173	**0.855**			Yes
SR	0.336	0.294	0.542	−0.310	**0.726**		Yes
TE	0.101	0.157	0.185	−0.011	0.205	Single item	Yes

Note: This table reports the square root of average variance extracted (AVE) value for each construct and its correlations with other constructs. The square root of AVE values is shown on the diagonal and printed in bold. The non-diagonal elements represent correlations of a construct with other constructs. The discriminant validity is met when the square root of AVE of a construct is greater than its correlation coefficients with other constructs [76].

Table 3. HTMT criterion analysis for assessing discriminant validity.

	ARAD	AROT	DL	HERD	SR	TE
ARAD						
AROT	0.463					
DL	0.456	0.589				
HERD	0.165	0.186	0.212			
SR	0.353	0.324	0.597	0.353		
TE	0.117	0.172	0.193	0.014	0.226	

Note: The HTMT ratio of correlations between the model's constructs are reported in this table. The HTMT value of less than 0.85 indicates discriminant validity [79].

Table 4. VIF values for examining multi-collinearity.

	ARAD	AROT	DL	SR	TE
SR	1.375	1.504	1.692		1.116
HERD		1.094		1.094	

Note: This table shows the variance inflation factor (VIF) values of exogenous constructs (given in the column) with respect to their endogenous constructs (given in raw wise) for the examination of multicollinearity. The VIF value of less than 5 indicates the absence of multi-collinearity [80,81].

7. Discussion of Results on Learning Behavior

Figure 2 depicts the main results relating to the investors' learning behavior examined in this paper. R^2 values of SR and HERD constructs are, respectively, 37.5 percent and 14.8 percent. Q^2 values of SR and HERD constructs are respectively 0.176 and 0.097, which indicate an acceptable level of the path model's predictive accuracy and relevance [66]. The estimates of path coefficients, their significance, and effect sizes are discussed below to test hypotheses related to individual and social learning behaviors.

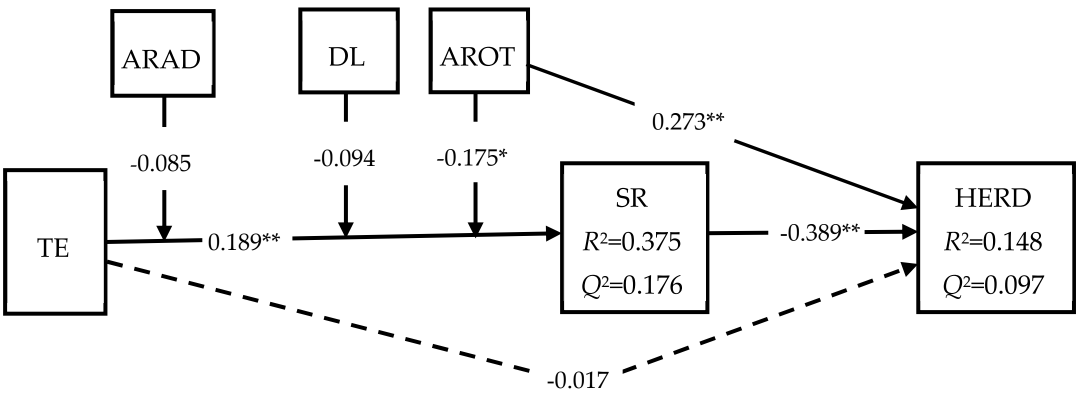

Figure 2. Main results of the investors' learning behavior. Note: The significance at 1 percent and 5 percent levels are denoted by ** and *, respectively.

7.1. Investors' Individual Learning Behavior

Concerning the results related to the individual learning behavior, presented in Table 5, the trading experience has a significant positive impact on the extent of self-reflection, which is consistent with H1. An increase in one standard deviation of the TE construct increases the SR construct by an 18.9 percent standard deviation ($f^2 = 0.048$, $p < 0.01$). In addition, confirming H2, the results reveal that an increase in one standard deviation of the SR construct decreases the HERD construct by a 38.9 percent standard deviation ($f^2 = 0.161$, $p < 0.01$). In line with H3, the SR construct mediates the relationship between TE and HERD constructs at a 5 percent level of significance. However, as shown in part A of Table 5, the evidence does not support a direct effect of the trading experience on minimizing herd bias (TE→HERD). Thus, it confirms the full-mediation of SR on the relationship between TE and HERD [83].

Table 5. Estimates of the model's path coefficients, their significance, and effect sizes relating to individual learning behavior.

Hypothesis	Path	Path Coefficient	Standard Error	*t*-Value	*p*-Value	Decision	f^2
Part A: Effect of the trading experience on self-reflection and herd bias							
H1	TE→ SR	0.189	0.068	2.640	0.004 **	Accept	0.048
H2	SR→ HERD	−0.389	0.090	4.294	0.000 **	Accept	0.161
H3	TE→ SR→ HERD	−0.069	0.033	2.080	0.019 *	Accept	
	TE→ HERD	−0.017	0.117	0.153	0.439		
Part B: Moderating effect of an authentic relationship with the investment advisor on self-reflection							
H4	ARAD × TE→ SR	−0.085	0.085	1.012	0.156	Reject	0.006
	ARAD × TE→ SR→ HERD	0.033	0.034	0.977	0.164		
	ARAD→ SR	0.068	0.067	1.017	0.154		0.006
	ARAD→ SR→ HERD	−0.026	0.024	1.025	0.153		
Part C: Moderating effect of the authentic relationship with other investors on self-reflection							
H5	AROT × TE→ SR	−0.175	0.083	2.169	0.015 *	Reject	0.027
	AROT × TE→ SR→ HERD	0.069	0.037	1.856	0.032 *		
	AROT→ SR	−0.028	0.073	0.432	0.333		0.001
	AROT→ SR→ HERD	0.011	0.028	0.454	0.325		
Part D: Moderating effect of desire for learning on self-reflection							
H6	DL × TE→ SR	−0.094	0.100	0.931	0.176	Reject	0.007
	DL × TE→ SR→ HERD	0.038	0.042	0.865	0.194		
	DL→ SR	0.404	0.082	5.016	0.000 **		0.165
	DL→ SR→ HERD	−0.159	0.053	2.986	0.001 **		

Note: This table reports the hypothesis testing results related to individual learning behavior. The model hypothesizes that TE is positively related to SR (H1), which, in turn, is negatively related to HERD (H2). It also assumes SR mediates the relationship between TE and HERD (H3). Furthermore, ARAD, AROT, and DL have moderating effects on the relationship between TE and SR (as reflected by H4, H5, and H6, respectively). The significance at 1 percent and 5 percent levels are denoted by ** and *, respectively. f^2 denotes the effect-size of the path's exogenous variable on its endogenous variable. As a rule of thumb, f^2 values of 0.02, 0.15, and 0.35 represent the cut-off values for small, medium, and large effects [84].

Then, moderating effects of ARAD, AROT, and DL constructs on the relationship between TE and SR, as reflected by H4, H5, and H6, are assessed. The estimates, given in parts B, C, and D of Table 5, reveal that these moderating effects are absent in the individual learning process during the period of the study. However, as shown in part D, the DL construct has a direct positive effect on the SR construct (f^2 = 0.165, $p < 0.01$), which, in turn, has a negative impact on the HERD construct ($p < 0.01$). Hence, rather than being a moderating variable, DL should be considered as a direct predictor of SR since it has a negative effect on herd bias through the mediating effect of self-reflection.

Next, the size of the effects of predictor constructs on respective endogenous constructs, as reflected by f^2 given in Table 5, are examined. Accordingly, the DL construct has the largest effect on the SR construct with an f^2 value of 0.165, which can be classified as a medium effect based on the cut-off values given by Cohen [84]. Nevertheless, the effect size of TE on SR appears to be small (f^2 = 0.048), while the moderating variables—ARAD and AROT—indicate no effects. The small effect size of TE on SR could be attributed to the uncertain market conditions prevailed during the period of the study. As discussed in Section 5.2, the uncertainty caused investors to become more risk averse and reduce their stock holding, which resulted in a lower trading frequency during this period. As a consequence, investors exhibited a lower tendency to be involved in stock trading, which shows a small effect of their trading experience in the self-reflection process. In addition, the lower trading frequency would have reduced their interaction with the investment advisor to a considerable level, which could be attributed to the absence of the moderating effect of ARAD in the self-reflection of experiences. Furthermore, as a frontier market, unsophisticated investors dominate the CSE. Hence, an investor's peer-relationships (AROT) may not provide quality information to strengthen his/her learning process, which results in an absence of the moderating effect of AROT in the self-reflection process.

7.2. Investors' Social Learning Behavior

The model assumes that the AROT construct is negatively related to the HERD construct in an investor's social learning process, as reflected by hypothesis H7. The results, reported in Table 6, do not provide support for this hypothesis, which indicates the absence of social learning behavior among the respondents. It is, however, interesting to note that the results rather confirm for an increase of herd bias from the peer-relationships, as reflected by the positive significant coefficient of the path AROT→HERD. Accordingly, it shows that an increase in one standard deviation of the AROT construct increases the HERD construct by a 27.3 percent standard deviation ($f^2 = 0.072$, $p < 0.01$). The uncertain market conditions prevailed during the period of the study and the dominance of unsophisticated investors could be considered as possible explanations for this increased herd tendency from peer-relationships. Therefore, in line with the herding literature, it is evident that uncertain market conditions motivate investors to disregard their own information and imitate others' behaviors when trading stocks.

Table 6. Estimates of the model's path coefficient, its significance, and effect size relating to social learning behavior.

Hypothesis	Path	Path Coefficient	Standard Error	*t*-Value	*p*-Value	Decision	f^2
H7	AROT→ HERD	0.273	0.077	3.339	0.000 **	Reject	0.072

Note: This table reports the hypothesis testing results related to the social learning behavior. The model hypothesizes that AROT is negatively related to HERD (as reflected by H7). The significance at 1 percent is indicated by **. f^2 denotes the effect-size of the path's exogenous variable on its endogenous variable. As a rule of thumb, f^2 values of 0.02, 0.15, and 0.35 represent the cut-off values for small, medium, and large effects [84].

7.3. Diversity of Learning with Respect to Investors' Demography

The hypothesis H8 is concerned with finding whether the level of SR varies between male and female respondents, and among their different age groups and education levels. The Independent sample *t*-test was conducted to check whether SR is significantly different between male and female investors (Table 7), while the one-way ANOVA test was performed to find whether SR significantly varies among different age groups and education levels (Table 8). The results show that the level of SR varies among different education levels. However, the same is not evident between male and female respondents and among their different age categories.

Table 7. Test of equality of SR between male and female investors.

Investor Group	Mean	Standard Deviation	Standard Error of Mean	*t*-Value	*p*-Value
Male	3.926	0.559	0.048	1.521	0.130
Female	3.770	0.802	0.109		

Note: This table shows the results of the independent sample t-test conducted for examining whether SR is different between male and female investors. The null hypothesis that mean values between male and female groups are equal, is not rejected at the 5 percent level of significance.

Table 8. Test of equality of SR among different age groups and education levels.

		Sum of Squares	Mean Square	*F*-Value	*p*-Value
Age and SR	Between Groups	0.884	0.221	0.535	0.710
	Within Groups	76.026	0.413		
Education and SR	Between Groups	17.359	4.340	13.409	0.000 **
	Within Groups	59.551	0.324		

Note: This table presents the results of the one-way ANOVA test to examine whether SR varies among different age groups and education levels. The significance at 1 percent level is denoted by **.

7.4. Comparison of Results with Previous Studies on the CSE

The results of this study show that investors' peer relationships drive herd behavior, whereas their self-reflection of experiences reduces herding when trading stocks. When concerning the magnitude of these two contradictory effects on herding, the effect-size of the self-reflection (f^2 = 0.161) appears to be higher than that of the peer relationships (f^2 = 0.072), which indicates a declining herd tendency at the aggregate market level. These results support the findings of the studies conducted by Shantha [8] and Xiaofang and Shantha [10]. Both of these studies find that herd tendency is strong during the periods of political uncertainty of the country (2000–2009) and the market bubble and crash (2009–2012), whereas it declines and disappear afterwards. Therefore, the findings of this study confirm that the investors' learning from their past experiences is the main reason for herding to decline and disappear during the past few market periods. Accordingly, it is evident that investors have learned the irrationality of herding from their past experiences. As a consequence, they tend to shift away from such irrational behavior when trading stocks.

8. Conclusions and Implications

To the best of my knowledge, this work is the first to show the link between the learning behavior of individual investors and its impact on herd bias. In view of that, it extends the previous studies of Shantha [8] and Xiaofang and Shantha [10] by providing empirical evidence on factors that ground for the declining herd behavior in the market. Of the eight hypotheses formulated in this study, six hypotheses (from H1 to H6) intend to examine the individual learning behavior as well as one hypothesis (H7) for the social learning behavior and one hypothesis (H8) for the analysis of the learning-diversity with respect to the demography of the investors. The main conclusion are as follows.

- The results confirm the hypotheses from H1 to H3, indicating a full mediation effect of investors' self-reflection on the relationship between their trading experience and herd bias. Hence, challenging the reinforcement learning (trial-and-error behavior) assumed by the previous studies conducted on the agent-based financial markets, the findings reveal that past trading experiences do not directly produce learning. Rather, the experiences are to be cognitively reflected (that is, self-reflection) to yield learning to reduce behavioral biases.
- However, findings do not support the moderating effects of investors' authentic relationships with investment advisors and peer investors, as reflected by the hypotheses H4 and H5, respectively. The uncertainty of market conditions caused the investors to reduce their risk appetite, which led to a low level of stock holding and trading frequency prevailing during this period. As a consequence, they may have maintained a low level of interactions with their investment advisors, which results in an absence of learning effects from the relationships with the advisors. Furthermore, since the CSE is a frontier stock market, a category of markets typically dominated by unsophisticated investors, the learning effect is absent through their peer-relationships. Accordingly, this evidence indicates that market conditions affect the extent of learning that occurred within an individual investor.

- Despite the absence of the moderating effect, as reflected by the hypothesis H6, the evidence shows that an investor's desire for learning has a direct influence on the self-reflection process. Accordingly, during the period of the study, the individual learning appears to have taken place through the self-reflection of past trading experiences, which is induced by the desire for learning. Furthermore, supporting the hypothesis H8, the results reveal that the extent of the self-reflection varies with respect to the investor's level of education.
- Invalidating the hypothesis H7, the findings indicate that the social learning is absent among the investors due to the dominance of unsophisticated investors in the market. It is evident that herd bias tends to increase among investors through these peer-relationships.

The findings of this paper also provide the following implications for practice.

- Consistent with the AMH, the success of an investor is highly dependent on the ability to learn and adapt to dynamic market conditions with feasible investment strategies. Stock exchanges conduct regularly educational programs to improve the financial literacy of investors to facilitate them to achieve a higher investment performance. The findings suggest that these educational initiatives should be designed to empower them to learn by reflecting on their own experiences. Consequently, they will be able to effectively learn from their past trading experiences, which reduced the exposure to behavioral biases when trading stocks. Accordingly, enhancing the self-reflection capacity of investors should be a key focus of these educational programs. The increased sophistication of investors and their stock market participation will take place while enabling them to engage in social learning through their peer-relationships.
- The investment advisors should continuously involve in building up strong client-relationships by strengthening the interaction, cooperation, and mutual trust with their clients. As a result, the clients will regularly interact with their advisors irrespective of the market conditions. It will support investors to improve their self-reflection capacity and arrive at better investment strategies for adapting to dynamic market conditions.

Hence, when the above implications are incorporated into the initiatives of stock exchanges and investment advisors, it can be expected that the sophistication of investors and their stock market participation will be enhanced. As stated in Sections 1 and 2.1, these will improve the ability of investors to recognize companies' sustainable development endeavor, which facilitates the companies to finance such developments at a lower cost. Accordingly, the investor learning behavior would eventually result in broader access to finance at lower cost so that sustainable economic development could be promoted.

9. Limitations and Directions for Future Research

This study has been conducted on a frontier market focusing a period over which its trading environment is highly uncertain. Hence, in terms of the type of the market and its environmental conditions, it is an ideal context for studying herd bias. However, it is subject to the following limitations. The findings of this study may not be generalizable to developed and emerging markets due to differences in investment and regulatory environment operating in those markets. In addition, the learning behavior has been studied by integrating its effects on herd bias, which is one of many forms of behavioral biases to which investors are exposed when trading stocks. Thus, the nature and extent of the learning may be different when the other types of behavioral biases are examined. Furthermore, the unit of analysis considered in this study is the individual investor. Hence, the results of this study may not be generalizable to predict the learning behavior of other investor-types such as institutional investors. Accordingly, future works can contribute to overcome these limitations by extending similar studies to other categories of markets (developed and emerging markets), different forms of behavioral biases (for example, heuristic and prospect biases), and other investor-types (for example, institutional investors and financial analysts).

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Measurement Scales

Table A1. Question items of the model's constructs.

Construct and Item Code	Item Wording	Source
	Trading experience (TE)	
TradeYrs	How long have you been investing in the stock market? (State in number of years)	Abreu and Mendes [53], Mishra and Metilda [54]
	Self-reflection (SR)	
	How would you respond to your past stock trading experiences?	Kember, Leung, Jones, Loke, McKay, Sinclair, Tse, Webb, Yuet Wong and Wong [55]
Sr_1	I sometimes question the way others do trading and try to think of a better way.	
Sr_2	I like to think over what I have been doing and consider alternative ways of doing it.	
Sr_3	I often evaluate my past stock trading so I can learn from it and improve my next trading experience.	
Sr_4	As a result of my trading experience, I have changed the way I make trading decisions.	
Sr_5	My experience has challenged some of my firmly held ideas and beliefs.	
Sr_6	As a result of the experience, I have changed the way I trade stock.	
Sr_7	I have discovered faults in what I had previously believed to be right.	
	(1 = Strongly disagree, 5 = Strongly agree)	
	Herd bias (HERD)	
	Please indicate the extent to which you agree with the following.	Waweru, Munyoki and Uliana [57]
Herd_1	I would invest stock by following my friends' recommendations.	
Herd_2	I would buy the stocks whose prices have risen for a period.	
Herd_3	I would follow the market trend when buying/selling stocks.	
	(1 = Strongly disagree, 5 = Strongly agree)	
	Desire for learning (DL)	
	Please indicate to what extent you feel about the following.	Fisher and King [60]
Dl_1	I want to learn new information	
Dl_2	I enjoy learning new information	
Dl_3	I have a need to learn	
Dl_4	I enjoy a challenge	
Dl_5	I do not enjoy studying	
Dl_6	I critically evaluate new ideas	
Dl_7	I learn from my mistakes	
Dl_8	I need to know why	
Dl_9	I am open to new ideas	
Dl_10	When presented with a problem I cannot resolve, I will ask for assistance (R)	
	(1 = Strongly disagree, 5 = Strongly agree)	

Table A1. *Cont.*

Construct and Item Code	Item Wording	Source
Authentic relationship with investment advisor (ARAD)		
	How would you describe your relationship with your investment advisor?	Kale, Singh and Perlmutter [63]
Arad_1	I would let my adviser decide everything.	
Arad_2	I prefer to ask my adviser's opinion for trading.	
Arad_3	I would trust my adviser.	
Arad_4	My adviser provides me with information important to make my trading decisions.	
Arad_5	My adviser cooperates and shares ideas, feelings, beliefs, etc. (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?	Kale, Singh and Perlmutter [63]
Arot_1	Friendly and can talk about difficulties personally	
Arot_2	Mutually trusting	
Arot_3	Mutually respectful	
Arot_4	Highly give-and-take	
Arot_5	Share ideas, feelings, beliefs, etc. (1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Very often, 5 = Always)	
Socio-demography		
Age	Please indicate your age (less than 25 years, 25–34 years, 35–44 years, 45–54 years, and 55 years or above)	
Gender	Please indicate your gender (male, female)	
Marital status	Please indicate your marital status (married, unmarried)	
Education	Please indicate your highest academic qualification (O/L, A/L, diploma, degree, postgraduate diploma, MBA/MSc, PhD) Please state your highest professional qualification, if any.	
Occupation	Please indicate your current occupation (Private sector employee, public sector employee, retired, self-employed, unemployed)	
Investment profile		
Trading frequency	How often do you buy or sell stocks? (occasionally, once a month, once a week, 2–3 times a week, daily)	
Risk appetite	How do you think your best friend would describe you? unwilling to take risks willing to take modest risks but only after careful consideration and professional advisement willing to take modest risks after some thought willing to take substantial risks after careful consideration and professional advisement someone who embraces risk, perhaps without sufficient consideration	
Stock-holding	Please indicate the percentage of your wealth invested in stocks?	

Appendix B. Demography and Investment Profile of Survey Respondents

Table A2. Demography of Survey Respondents.

		No. of Participants	Percentage of Respondents
Gender	Male	135	71.4%
	Female	54	28.6%
Age	Less than 25 years	13	6.9%
	25–34 years	64	33.9%
	35–44 years	46	24.3%
	45–54 years	38	20.1%
	55 years or above	28	14.8%
Marital Status	Married	131	69.3%
	Unmarried	58	30.7%
Highest academic qualification	A/L	44	23.3%
	Diploma	46	24.3%
	Degree	59	31.2%
	Postgraduate Diploma	10	5.3%
	MBA/MSc	30	15.9%
	Ph.D	0	0.0%
Occupation	Private sector employee	148	78.3%
	Public sector employee	9	4.8%
	Retired	11	5.8%
	Self-employed	16	8.5%
	Unemployed	5	2.6%

Table A3. Respondents' Investment Profile.

		No. of Participants	Percentage of Respondents
Trading experience	2 years or less	9	4.8%
	3–7 years	46	24.3%
	8–12 years	79	41.8%
	13–17 years	34	18.0%
	18 years or above	21	11.1%
Trading frequency	Occasionally	112	59.3%
	Once a month	17	9.0%
	Once a week	18	9.5%
	2–3 times a week	24	12.7%
	Daily	18	9.5%
Risk Appetite	Very low risk taker	26	13.8%
	Low risk taker	62	32.8%
	Average risk taker	43	22.8%
	High risk taker	53	28.0%
	Very high risk taker	5	2.6%
Proportion of wealth invested in stocks	Less than 5%	38	20.1%
	5–15%	91	48.1%
	16–25%	26	13.8%
	26–40%	11	5.8%
	41–60%	15	8.0%
	More than 60%	8	4.2%

Appendix C. Cross-Loadings of Indicator Items to Latent Variables

The following table presents the loading values of each indicator item to its own construct and other constructs of the model. The discriminant validity is established when the loadings of indicator items to its own construct are higher than those of other constructs [77,78].

Table A4. Cross-loadings of indicator items.

Construct	Indicator Item	ARAD	AROT	DL	HERD	SR	TE
ARAD	Arad_1	0.866	0.378	0.437	−0.121	0.314	0.043
	Arad_2	0.777	0.188	0.225	−0.124	0.161	0.096
	Arad_3	0.811	0.307	0.303	−0.025	0.230	0.135
	Arad_5	0.820	0.410	0.353	−0.076	0.332	0.081
AROT	Arot_1	0.344	0.628	0.312	−0.028	0.267	0.125
	Arot_2	0.276	0.842	0.344	0.263	0.131	0.096
	Arot_3	0.373	0.838	0.525	0.096	0.272	0.114
	Arot_4	0.277	0.819	0.418	0.170	0.217	0.072
	Arot_5	0.347	0.794	0.430	0.047	0.263	0.213
DL	Dl_1	0.319	0.316	0.799	−0.198	0.456	0.112
	Dl_2	0.354	0.461	0.819	−0.122	0.433	0.169
	Dl_3	0.369	0.378	0.806	−0.121	0.404	0.175
	Dl_4	0.288	0.434	0.827	−0.078	0.340	0.100
	Dl_6	0.292	0.467	0.748	−0.125	0.472	0.167
	Dl_7	0.365	0.386	0.733	−0.164	0.434	0.181
	Dl_8	0.279	0.389	0.763	−0.134	0.431	0.079
	Dl_9	0.363	0.452	0.788	−0.162	0.403	0.174
HERD	Herd_1	−0.111	0.069	−0.127	0.875	−0.259	−0.017
	Herd_2	0.015	0.232	−0.055	0.861	−0.250	0.001
	Herd_3	−0.193	0.035	−0.289	0.830	−0.290	−0.015
SR	Sr_1	0.112	0.066	0.341	−0.132	0.567	0.034
	Sr_2	0.121	0.119	0.318	−0.089	0.535	0.224
	Sr_3	0.293	0.279	0.508	−0.285	0.819	0.190
	Sr_4	0.333	0.260	0.445	−0.384	0.838	0.122
	Sr_5	0.140	0.110	0.223	−0.198	0.649	0.143
	Sr_6	0.308	0.199	0.377	−0.189	0.815	0.185
	Sr_7	0.283	0.350	0.460	−0.207	0.789	0.153
TE	TradeYrs	0.101	0.157	0.185	−0.011	0.205	1.000

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