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Self-attribution and overconfidence in Colombo Stock Exchange

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Abstract

The physiological behaviors in Colombo Stock Exchange to be discovered as they cause to have market anomalies in which is not technically driven and there are compared to other countries. The purpose of this study is to observe whether overconfidence bias and self-attribution bias exist in Colombo Stock Exchange. This study utilises the Structural Equation Modeling to analyse the collected data by using a questionnaire survey from 418 active individual investors in Colombo Stock Exchange. Out of the three stages of rational decision-making theory, it is observed that evaluating alternatives contribute to overconfidence bias and self-attribution biased significantly. Therefore, it is evidenced that if the investors do not concern on demand identification and evaluating alternatives correctly, investors may be influenced to overconfidence bias and self-attribution bias that the investors in Colombo Stock Exchange follow the theory of rational decision-making which related to evaluating alternatives. According to the findings of this study, there is a mixed result of both rational and irrational investor behavior. Hence, the investors in Colombo Stock Exchange display an apparently both rational and irrational behaviors in making investment decision processes. The findings of this study are imperative to investors, investment advisors, and policy makers etc. to have rational investment decisions in the Colombo Stock Exchange.

Keywords:- *Overconfidence, Self-attribution, Colombo Stock Exchange*

1 Introduction

According to rational decision theory, an individual attempts to solve problems by devising various strategies and following specific logical procedures, depending on the nature of the problem, the time, and the decision environment (Gianakis, 2004). Individual investors are seen as attempting to make rational decisions within the framework of bounded rationality framework (Simon, 1957), However, they frequently lack a critical understanding about the problem's definition, suitable criteria, and so on. People's rationality limits their judgment; therefore, they will forsake the optimal answer in favor of an acceptable or reasonable one, which is referred to as the decision makers satisfice (Caparrelli, 2004).

Kahneman (1979) offered crucial details about systematic biases that influence judgment. Investors, according to Thaler (1980), have limited willpower, therefore they prioritise current issues above future concerns, resulting in a variety of ways in which their short-term motives conflict with their long-term goals. Investors are known to have behavioral biases, even if their investment decisions are based on a rational decision-making process.

Rationality and market efficiency are two important assumptions in traditional finance theory and economic models. Traditional economic assumptions characterise humans as rational beings that strive to always maximise their utility. Behavioral finance proponents, on the other hand, continue to argue that investor behavior is influenced by several factors, including both rational and irrational thinking. They believe that market pricing isn't always a fair predictor of a company's underlying fundamental value, and that market prices and fundamental value might vary dramatically due to investor psychology (Asaad, 2012).

The adaptive market hypothesis (AMH), as formalised by Lo (2004), contends that market efficiency and inefficiency coexist in a rational manner. He elaborates on the topic of behavioural biases using the constrained rationality paradigm (Simon, 1957). The new viewpoint, which applies evolutionary ideas to financial markets, was offered by Farmer and Lo (1999) and Farmer (2002). Lo (2005), believe that the market will seek consummate balance or flawless efficiency. This makes it possible to interpret market efficiency much more flexibly. Through the concept of variable efficiency, AMH provides testable implications of time-varying return predictability based on market situations such as market crashes, bubbles, economic booms, and crises. The AMH can explain not only departures from the efficient market hypothesis (EMH) and behavioural regularities, but also how markets go from crowd wisdom to mob madness and again.

Apart from all behavioral patterns, the aspects of Sri Lankan people differ from other countries. Furthermore, there are various variables that belong to these behavioral factors (Samarakoon, 2016) and behavioral finance challenges the existing economic theories. As opposed to the findings suggested by the traditional economists, through the prospect theory behavioral finance justifies how emotions such as greed and fear come into play when investing. Studies show that individuals fear losing money more than earning them. Hence, they tend to make unjustifiable decisions such as selling stocks in bullish markets.

In to be discovered in depth as there are many inequalities compared to other countries (Gunathilaka, 2014). Thus, using data from the Colombo Stock Exchange (CSE), this study investigates the impact of behavioral characteristics that explain irrational conduct on individual investor investment decisions in Sri Lanka. Furthermore, there are various variables that belong to the behavioral factors. Thus, this study explores the impact of those variables on each behavioral factor and then explore the impact of these behavioral characteristics on individual investors' investment decisions. Cognitive biases are important study mediators in investor decision-making.

Self-attribution and overconfidence are two decision-making biases that have received a lot of attention in the research (Mushinada, 2019).

The major goal of this research is to investigate the interaction between rational decision-making and behavioural biases in the CSE. The empirical study will look at whether there are self-attribution and overconfidence biases in the Sri Lankan stock market, as well as whether individual investors make rational investment decisions in the CSE. This study's findings will aid investors in lowering the negative impact of behavioural biases on expected utility. Especially assist consultants in identifying market biases and developing appropriate investing strategies.

2 Literature review

A rational decision-maker bases his or her decision on logic and systematic decision-making procedures (Robbins, 2002). In the rational decision-making process, there are some well-established models with numerous decision stages. Mintzberg (1976) identified three basic stages in the rational decision-making process: identifying the problem, gathering relevant data, and evaluating possible solutions. Keeney (1998) and (Hammond, 2002) presented six method criteria to evaluate an effective rational decision in a similar way. Eight processes for decision-making were proposed by Daft (2003), Osland (2006), and (Robbins, 2002).

Though investors differ in their ideas, views, and preferences, rationality is concerned with the idea that these elements should be consistent (Shafir, 2002). According to Judge (2007), a rational decision entails a thorough and a rigorous decision-making procedure aimed at maximising predicted revenues. An EMH, which is also incorporated in traditional financial theory, is predicated on the assumption of rational investor behavior.

According to Fama (1965), no one can continually deceive the market to create excess profits in an efficient market when information is completely revealed.

Aside from that, to maximise earnings, the most rational investors can reflect market knowledge rapidly and independently. Individual investors who participate in selecting financial products always go through a conscious procedure that resembles logical investment decision-making. Bounded rationality was proposed by Simon (1957), which claims that managers make poor decisions due to a lack of information, insufficient time, and cognitive limitations.

The prospect theory was suggested by Kahneman (1979) to describe how people make decisions in ambiguous situations. According to the prospect theory, investors'psychological characteristics cause their genuine decision-making process to depart from rationality, which is comparable to the dispute of (Simon, 1957) concerning bounded rationality.

According to Metawa (2019), investors' decision-making processes are frequently simplified, and they are prone to behavioral heuristics that lead to systematic errors and satisfied investment assessments, but not to optimal conclusions. Investors' value functions have risk perception asymmetries built in, causing them to make investment decisions based on their institutions and previous investment experiences rather than logical analysis and objective reasons.

The number of rivals, the volume of accessible profit opportunities, and the flexibility of market players are all factors that influence market efficiency (Lo., 2005). The paradigm of AMH, in efficient markets, different investors make mistakes and learn to adjust their behavior as a result. Profit prospects are continually being produced and disappearing from the perspective of progress. Investment methods that are based on the current market condition. AMH, on the other hand, as innovation is a platform for surviving and adapting to market volatility, it denotes difficult market dynamics that demand active portfolio management.

As per the Mushinada (2019), positive outcomes are often attributed to personal characteristics, whereas unfavorable outcomes are attributed to bad luck or other reasons is referred to as self-attribution bias. Individuals would take credit for their accomplishments while blaming failures on other circumstances (Mushinada, 2019). Self-attribution bias is classified into two types: self-enhancing bias, which refers to people's irrational rejection of responsibility for failure, and self-protecting bias, which refers to people's tendency to claim an unjustified amount of credit for their performance.

Self-attribution bias was introduced into standard models by some behavioral models that aimed to provide a theoretical framework for empirical return anomalies (Daniel, 1998). The stationary and dynamic equivalents of overconfidence and self-attribution are overconfidence and self-attribution, according to (Hirshleifer, 2001). Further, individuals develop to be overconfident because of self-attribution rather than joining on a correct self-assessment (Li, 2010).

Overconfidence bias implies that investors routinely misinterpret publicly available data and place undue emphasis on their personal information (Daniel, 1998). According to Mushinada (2019), individual investors are one of the stakeholders implicated in this overconfidence. According to the study, investors are overconfident in their abilities, expertise, and future ambitions (Odean, 1998). As a result, traders become more aggressive in their trading, putting a price on their expected utility. Other researchers have discovered that overconfidence impacts trading volume and frequency, confirming prior findings that volatility and trade volume have a relationship (Benos, 1998).

According to Glaser (2007), high overconfidence investors tend to trade in huge volumes. Overconfidence, on the other hand, varies according to culture. According to Weber (2002), large-volume traders are more prone to have a high level of overconfidence.

Fama (1965) specified that, "An efficient market is one in which a large number of rational, profit-maximising individuals are actively competing, each attempting to predict future market values of particular securities, and where critical current information is nearly free to all participants". In an efficient market, competition among the many smart participants results in a situation where, at any given time, the effects of information based on both past events and events that the market predicts will occur in the future are already reflected in the actual values of individual securities. In other words, the present price of an asset in an efficient market is an accurate estimate of its inherent value at any given time.

According to (Tan, 2008), the term "efficiency" refers to the fact that, as compared to other investors, investors have little chance of making anomalous profits from capital market transactions and say that the question of whether markets are efficient in the ways that EMH claims is still open.

This points to the frequency of EMH during periods of steady and stationary market conditions, and in the relevant literature, there has been a flood of research that find considerable evidence of AMH in stock markets (Mushinada, 2019).

3 Research methodology

The study attempts to determine whether individual investors have complicated rational and illogical thinking logics and adjust to market dynamics. Furthermore, the current study was based on a study conducted by Mushinada (2019) & the procedure, and questionnaire were used in this study with modifications of the base study which was conducted by Mushinada (2019) as per the Sri Lankan context.

In contrast to earlier research that has focused solely on detecting behavioral biases and their effects, this study uses Structural Equation Modelling (SEM) to develop a full path linking the three stages of investors' rational decision-making process and two behavioral biases. The underlying processes are described by a set of structural equations that can be graphically displayed to aid in the development of a theoretical framework. SEM provides for simultaneous evaluation of factor loadings and measurement error variance and testing the significance of correlations between latent variables of interest and causality direction.

3.1 Sample

The primary data is gathered by presenting a structured questionnaire to "active investors" (those who have been involved in stock trading for at least a year): Annual Report of CSE 2019. This is to collect information regarding investors' behavioral biases and their capacity to adjust to market changes while attempting to make logical decisions. Study population comprised of every active individual investor in CSE. The decision on sample size determined mainly by the size of the population considered. Convenient sampling technique used, and the sample size of this study comprised with 418 respondents. Since a sample size between to “200 to 400” it is suitable for SEM using ordinal data. It has been further pointed out that when the sample size exceeds 400 to 500 responses, SEM analysis becomes too sensitive with the result that almost every difference is detected. These findings appear to be supported by the sample size of this current study. As a large enough sample size allows for greater confidence and accuracy by reducing the margin of error and increasing the confidence limits, the above sample size can be considered adequate for the purpose of this study.

3.2 Questionnaire

With the requirement analysing investors' psychological attitudes toward decisions relating to their investments, they are widely assumed through the primary data it can correctly that primary data can correctly replicate the innermost motive. Based on the structured questionnaire, which used by (Mushinada, 2019) is used by modifying according to this study, 19 items were constructed with the study's aims and focus on mind to collect primary information from CSE investors and elicit their responses. The possessions go through four stages such as (1) identification and degree of searching information (2) degree of evaluating alternatives (3) overconfidence bias and self-attribution bias (4) demographic factors, personal information, and current financial position.

31 items were included in the questionnaire and to measure respondents' psychological agreement based on the observed factors, 21 items in the questionnaire use seven-point Likert-type scales: Strongly Disagree (1) to Strongly Agree (7). A pilot study was undertaken after the questionnaire was completed using two respondents and the issues that they suggested were taken into

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consideration. After the slight modifications, the questionnaires were administered to the respondents as per the initial plan.

3.3 Data analysis

The gathered information is examined by utilising SPSS and AMOS statistical packages. AMOS is an additional SPSS module and is uniquely utilized for SEM, path analysis, and Confirmatory Factor Analysis (CFA). The researchers used AMOS Graphic to effectively, precisely, and efficiently model and analyse the inter-relationships among latent components. More crucially, the model's many equations of inter-relationships are computed at the same time. Furthermore, rather than writing equations or inputting commands, researchers used the AMOS Graphic interface to build path diagrams using drawing tools. CFA was used to validate the measurement model of a latent component.

The SEM incorporates quantitative data as well as correlational and causal assumptions into the model. SEM starts with a hypothesis that the researcher wants to test to see if there is a link between the constructs of interest in the study. A set of items in a questionnaire are used to measure the constructs of interest. Each item's measuring scale should be either interval or ratio.

The ideal measurement range is 1 to 7, which ensures that the data is more independent and meets the parametric analysis criterion. The construct is for an indirectly measured score, while the variable is for a directly measured score. In reality, the construct is nothing more than a hypothetical concept of something, or the respondents' perspective of a certain issue. The respondent's response to a series of items in a questionnaire is used to measure a concept.

In the context of AMH, SEM is utilised to better understand the relationship between investors' rational decision-making process and behavioral biases. The SEM model can be divided into two parts: a measurement model and a structural model. The measurement model defines the relationship between observable and unobserved variables. As a result, the measurement model depicts the CFA model, which specifies the pattern through which each measure loads on a certain factor.

The structural model, on the other hand, establishes relationships between unobserved variables. As a result, it explains how some latent variables influence changes in the values of other latent variables in the model, either directly or indirectly. Because the study focuses on the causal relationship between rational decision-making and two behavioral biases, and whether individual investors are rational or not, it is used to develop a full latent variable model that includes both measurement and structural models, allowing the data to speak for itself. The work of building a full SEM measurement model consists of two parts: determining the number of indicators to use in measuring each construct and determining which items to utilise in formulating each indicator.

Researchers looked at each construct's measurement model to see how well the generated items matched the underlying construct. CFA is used to do the analysis. The challenges of construct validity and reliability would be addressed through the CFA procedure. The researchers looked at the factor loading for each item as well as the construct's fitness indexes. The item with low factor loading should be removed from the measurement model since it causes poor fitness indexes for the construct. The model is re-specified after deletion, and the fitness indexes improve.

For the study, items having a Cronbach's alpha of 0.5 or above are kept. The extent to which a latent component may explain the variation of a measured variable is represented by SMCs. It represents how well an object measures a construct from the standpoint of measurement. Items having SMCs of less than 0.3 are removed from consideration. For each latent variable, the absolute values of skewness and kurtosis are less than 3 and 10, respectively.

To assess construct validity, the study used a sample of 418 investors to conduct CFA. Construct reliability (CR) is a convergent validity metric that should be at least 0.7 to demonstrate appropriate convergence or internal consistency. Estimates of standardised factor loading should be 0.5 or greater (Hair, 2009).

Demand identification is an exogenous latent variable in the measurement model, whereas searching for information, evaluating alternatives, biased self-attribution, and overconfidence are endogenous latent variables.

The structural model is created to depict the structural links between the latent variables that will be accurately estimated using equation (01).

$$\boldsymbol{\eta_i = \beta_{ij}\eta_j + \gamma_{ij}\xi_j + \varsigma_i} \textbf{ where i, j = 1, 2, 3, ...} \text{(01)}$$

where ξj represents an exogenous latent variable, demand identification; and ηj represents an endogenous latent variable, searching information, evaluating alternatives, biased self-attribution, and overconfidence. γij denotes the regression coefficient of ξj on ηi; βij denotes the error variance of the equation; and ςi denotes the regression coefficient of ηj on ηi

4 Discussion

4.1 Measurement model

Figure 1 depicts standardised estimates of correlation between demand identification, information search, and alternative evaluation that are close to or greater than one, indicating the possibility of multicollinearity. The reason for this could be the close interdependence of these three factors, which underpins a strong theory of rational decision-making by (Mintzberg, 1976).

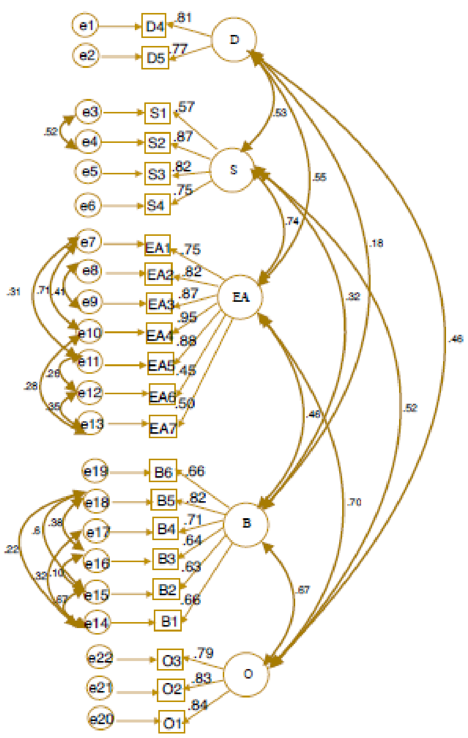

Figure 1: Final overall measurement model

Source: Research data

Figure 1 illustrates initial model which includes five variables: Demand identification (D), Searching information (S), Evaluating Alternatives (EA), Self-attribution bias (B) and finally Overconfidence bias (O).

Coding of each dimension and variables with factor loading are produced in Table 1 below.

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Table 1: Factor loadings of final measurement model

	Item No.	Variable	Factor Loading
1.	D4	Demand identification (D)	0.813
2.	D5	Demand identification (D)	0.770
3.	S1	Searching Information (S)	0.571
4.	S2	Searching Information (S)	0.868
5.	S3	Searching Information (S)	0.823
6.	S4	Searching Information (S)	0.752
7.	EA1	Evaluating Alternatives (EA)	0.749
8.	EA2	Evaluating Alternatives (EA)	0.817
9.	EA3	Evaluating Alternatives (EA)	0.868
11.	EA4	Evaluating Alternatives (EA)	0.948
12.	EA5	Evaluating Alternatives (EA)	0.875
13.	EA6	Evaluating Alternatives (EA)	0.500
14.	EA7	Evaluating Alternatives (EA)	0.501
15.	B1	Self-attribution Bias (B)	0.655
16.	B2	Self-attribution Bias (B)	0.632
17.	B3	Self-attribution Bias (B)	0.636
18.	B4	Self-attribution Bias (B)	0.707
19.	B5	Self-attribution Bias (B)	0.822
20.	B6	Self-attribution Bias (B)	0.663
21.	O1	Overconfidence bias (O)	0.836
22.	O2	Overconfidence bias (O)	0.829
23.	O3	Overconfidence bias (O)	0.794

Source: Research data

CFA investigates each factor's loading to determine whether it is above the required threshold levels. Factor loading (Standardised regression weights), Table 1 shows the final measurement model.

As a result, all items scored factor loading greater than 0.5 and were retained in the model. Analysing measurement models also entails evaluating the model's GOF indices. Table 2 displays the model fit indices of the initial model.

Table 2 contains four absolute fit indices: chi-square significance, relative chi-square, and Root Mean Square Error of Approximation (RMSEA). The Comparative Fit Index (CFI) is one of the incremental fit indices. The table also includes the Parsimonious Goodness of Fit Index (PGFI) and the Parsimony Normed Fit Index (PNFI), which are measures of parsimony fit. The model's actual values are compared to the threshold values of each index. As a result, it is worth noting that the final measurement model meets all criteria.

Once the CFA procedure for each measurement model has been completed, certain measures that indicate the construct's validity and reliability must be computed. Measurement model analysis also includes an evaluation of construct validity and reliability. Table 3 presents the AVE, CR and Cronbach's alpha of the final measurement model.

As per the table 3, it shows that CR is greater than a threshold of 0.7, Hair et al. (2007) thus the measurement model is having high reliability. AVE is a measure of convergent validity which should be greater than the threshold of 0.5. The table shows that all the constructs are higher than the threshold. Based on AVE and CR, the researchers can conclude that the construct's convergent validity is adequate. Accordingly, the measurement model satisfies the criteria of CR, thus it can be concluded that the constructs of the measurement model have the convergent validity. All of the indicators indicate that the study can move forward with the development of the structural model.

Table 2: Final overall measurement model

Indices	Cut-off values and acceptable threshold levels	Final model values	Decision
Absolute Fit Indices			
Relative $\chi 2$ ($\chi 2$/df)	<5.00	4.074	Accepted
RMSEA	<0.01	0.080	Accepted
Incremental Fit Indices			
CFI	>0.9	0.903	Accepted
Parsimony Fit Indices			
PGFI	>0.5	0.634	Accepted
PNFI	>0.5	0.706	Accepted

Source: Research data

Table 3: Validity and the reliability of the measurement model

Variable	AVE	Construct Reliability	Cronbach's Alpha
Demand identification (D)	0.627	0.771	0.785
Searching Information (S)	0.581	0.844	0.825
Evaluating Alternatives (EA)	0.585	0.903	0.894
Self-attribution Bias (B)	0.500	0.843	0.840
Overconfidence bias (O)	0.672	0.860	0.860

Source: Research data

4.2 Structural model

Figure 2 depicts the structural routes and parameter estimations for the structural model. The structural model's structural relations and related statistics are presented in Tables 4 and 5.

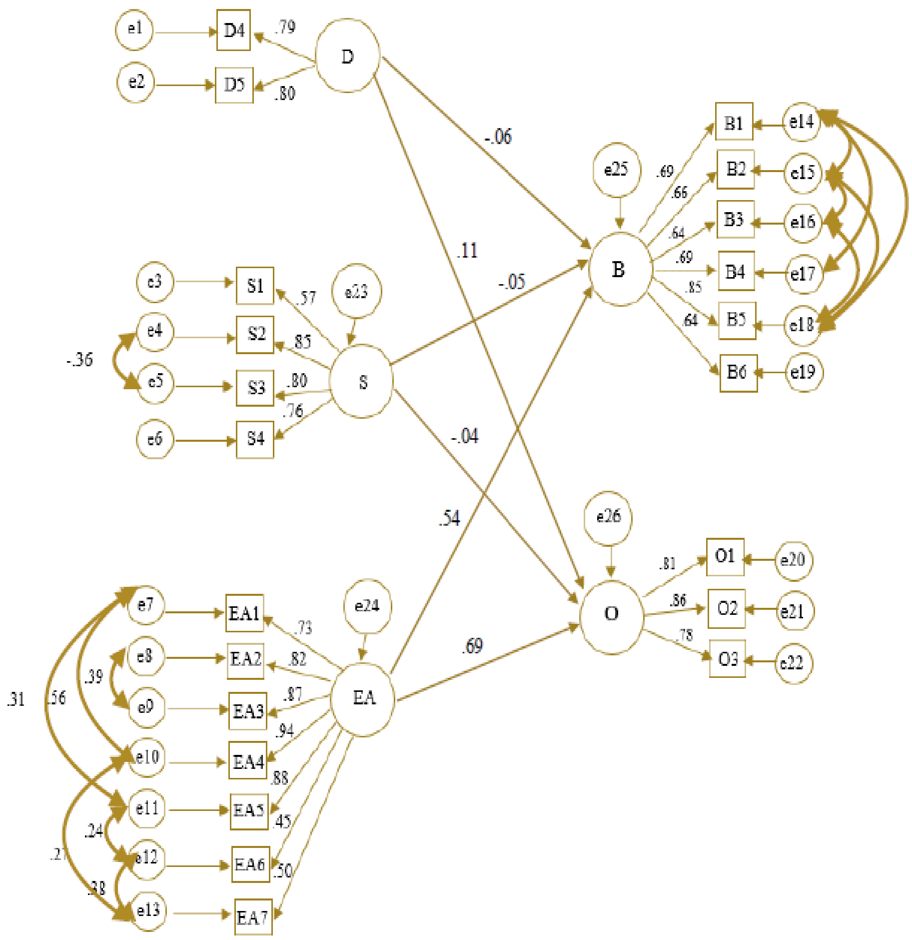

Figure 2: Structural Model
Source: Research data

Table 4: Regression results – impact of demand, search, and evaluate on self-attribution

Independent variable	Estimate	S.E	CR	P-Value
Demand Identification (Demand)	0.063	0.068	0.933	0.351
Searching Information (Search)	0.046	0.082	0.559	0.576
Evaluating Alternatives (Evaluate)	0.818	0.145	5.644	0.000

Source: Research data

Table 5: Regression results – impact of demand, search, and evaluate on overconfidence

Independent variable	Estimate	S.E.	CR	P-Value
Demand Identification (Demand)	0.117	0.063	1.845	0.065
Searching Information (Search)	0.033	0.076	0.439	0.661
Evaluating Alternatives (Evaluate)	1.106	0.148	7.463	0.000

Source: Research data

According to the structural model's findings, if investors do not focus on accurately evaluating alternatives, they may be exposed to behavioral biases, self-attribution, and overconfidence. At the same time, after they have experienced losses, they become cautious and re-evaluate the fundamentals of their investments. Investors are known to deviate from rationality due to cognitive biases such as self-attribution and overconfidence, yet they try to adjust to market dynamics. They would be more concerned about how it will affect their stock returns or utility.

5 Conclusion

Along with logical decision-making, investors are exposed to a variety of cognitive biases. Once they have experienced losses or unpredictable situations, they adapt to the altering environment. The study's findings are noteworthy and support the hypothesised hypothesis. This study's empirical findings contribute significantly to efforts to link rational decision-making with irrational investor behavior. Individual investors' investment activity may be characterised by sophisticated reasonable and irrational thinking logics. This agrees with Lin (2011) findings. The findings are also consistent with Simon (1957), who claimed that the existence of psychological anticipation is the foundation of bounded rational behavior.

The findings of the study are consistent with previous research on self-attribution and overconfidence. Investors are concerned about the influence of these cognitive biases on their stock returns or utility, and as a result, they adapt to shifting market dynamics because of AMH.

Similar to the finding that Sri Lankan stock market investors are overconfident, other emerging countries like Pakistan (Rehan & Umer, 2017), India (Mushinada & Veluri, 2019; Prosad, 2017) show the same result. Stock market investors in Sri Lanka needs to realise the fact that their investment decisions are hindered due to behavioural biases such as overconfidence and herding (Lasantha & Kumara, 2021). It is likely that Sri Lanka is an emerging economy, and overconfidence bias influences the investment decision making of stock market investors at the CSE.

If investors have behavioral biases, the CSE suffers. As a result, it is incumbent upon all stakeholders to exercise necessary prudence and care in this regard. The study's findings have important managerial implications for a variety of stakeholders, including individual investors, fund managers, and policymakers. Individual investors should conduct a post-analysis of each investment, become conscious of their previous behavioral errors, and begin responding to new market conditions. Restraining emotions and overcoming behavioral biases are frequently required for success. There is a proclivity to overtrade based on representativeness heuristics, which contributes to the disposition effect. They must invest for the long term, evaluate their risk tolerance, choose an appropriate asset allocation plan, and rebalance their portfolios on a regular basis. It is also suggested that before creating portfolios, fund managers strive to detect behavioral biases in their clients. To avoid a "wealth loss" situation for both investors and they must de-bias themselves by applying relevant knowledge and making reasonable investing selections. The existence of diverse behavioral biases must be taken seriously by regulatory agencies, which must apply standard norms used by worldwide financial markets. There should be a scientific system in place to educate investors about different behavioral biases and how they affect their expected benefit. Foreign institutional investors should be closely monitored, particularly for their regular sell-off operations during market collapses when outflows exceed inflows, to combat the stock market's ongoing volatility. Future studies on AMH should, however, be undertaken utilising individual account data or psychology study conducted through detailed questionnaires or well-designed trials.Studying on behavioral factors would have a knock-on effect for the investors, public, making maximum efficiency and effectiveness on allocated resources, public satisfaction, and high level of performance in the organisation leads to the sustainable growth at the end. Studying on behavioral factors is crucial and complex as it always unique to one another. This study aims at broadening knowledge of investors other stakeholders on employee investment decision making. This research also donates new knowledge to the developing body of literature of investment decision making the behavioral factors affecting to the decision making relating to the investments is much critical on growth in the CSE in Sri Lanka and contributing to the direction of developed capital market.

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