Impact of Behavioral Biases on the Profitability of Cryptocurrency Day Traders in Sri Lanka

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ABSTRACT

Cryptocurrency day trading has grown fast in Sri Lanka, but many day traders lose money. This study examines how three behavioral biases, herding behavior, heuristic biases, and prospect theory-based biases, affect the perceived profitability of cryptocurrency day traders in Sri Lanka. Earlier studies looked at how these biases affect general investment decisions, but no known study looked at how they relate to the profit of day traders in Sri Lanka. The study used a quantitative design. An online questionnaire was shared in cryptocurrency trading groups on social media, and 500 valid responses from active day traders were collected through non-probability sampling. Perceived profitability was measured by the traders' own ratings of their trading results, not by checked account data. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. All three biases had a positive and significant effect on perceived profitability. Herding behavior had the strongest effect ($\beta = 0.190$), followed by prospect theory-based biases ($\beta = 0.157$) and heuristic biases ($\beta = 0.142$). The three biases together explained 14.9 percent of the variance in perceived profitability. This result does not mean that biases raise real profit. It means that traders with stronger biases rate their own results higher. The heterotrait-monotrait (HTMT) ratio between heuristic biases and prospect theory-based biases was 0.919, so these two biases overlap, and their separate effects should be read with care. The study gives advice to traders, trading platforms, and regulators.

Keywords: *herding behavior; heuristic biases; prospect theory; perceived profitability; cryptocurrency day trading*

JEL Classification: *G11, G40, G41*

1. INTRODUCTION

Cryptocurrency is a digital and decentralized form of money. It does not need a central bank or a third party, such as a bank, to work (Manoj, 2023; Roza et al., 2024). Since Bitcoin started in 2009, the number of cryptocurrencies has grown very fast (Gunasena et al., 2024).

Cryptocurrency has also become popular in Sri Lanka in recent years. The value of the Sri Lankan rupee has fallen, and Gunasena et al. (2024) report that the number of cryptocurrency traders in Sri Lanka grew by 730 percent during the economic recession. They also report that Sri Lanka moved up to 49th place in the 2023 Global Crypto Adoption Index. These figures come from a 2024 source, and they may be different today. Cryptocurrency is still not legally recognized in Sri Lanka, but many traders use it through online platforms such as Binance (Manoj, 2023).

Day trading means buying and selling an asset within the same day. It can bring a big gain or a big loss in a short time (Roza et al., 2024). Studies show that day trading is risky and that only a few traders make a steady profit. Roza et al. (2024) found that 97 percent of traders who day traded for more than 300 days lost money in the end. Abarquez et al. (2025) found that only 44 percent of the cryptocurrency traders in a Philippine-based online community performed better than the market.

Cryptocurrency day trading is therefore an important area to study in Sri Lanka. The market is fast-growing, it is not regulated, and many traders may lose money. A better understanding of trader behavior can help traders, trading platforms, and regulators to make safer decisions.

Behavioral finance explains that investors do not always act in a rational way. Instead, biases in their thinking and their feelings affect them (Gunasena et al., 2024). Three important biases in cryptocurrency trading are herding behavior, heuristic biases, and prospect theory-based biases. Herding behavior happens when traders copy the actions of other traders instead of thinking on their own. Heuristic biases include overconfidence, anchoring, availability bias, representativeness, and the gambler's fallacy. Prospect theory-based biases include loss aversion, regret aversion, and mental accounting.

Gunasena et al. (2024) studied how these three biases affect the investment decisions of 158 Sri Lankan cryptocurrency investors. They found that heuristic biases and prospect theory-based biases had a significant effect, but herding behavior did not. However, their study looked at general investment decisions, not at the profit of day traders. Roza et al. (2024) studied the losses of day traders, but not in Sri Lanka. Abarquez et al. (2025) studied the profitability of cryptocurrency trading in the Philippines, but they did not include behavioral biases. No known study has looked at how these three

biases relate to the profitability of cryptocurrency day traders in Sri Lanka. This study fills that gap.

In this study, profitability means perceived profitability. It is the trader's own view of how profitable his or her trading is. The study does not measure real profit from trading accounts. This point is important, and it is kept clear in the title, the hypotheses, the results, and the discussion. The rest of this paper has six parts: Aims/Objectives, Theory, Methods, Results, Discussion, and Implications and Limitations.

2. Aims/Objectives

The research question of this study is: What is the impact of behavioral biases on the perceived profitability of cryptocurrency day traders in Sri Lanka?

The aim of the study is to examine how behavioral biases relate to the perceived profitability of cryptocurrency day traders in Sri Lanka. There are three specific objectives. The first objective is to examine the effect of herding behavior on the perceived profitability of cryptocurrency day traders in Sri Lanka. The second objective is to examine the effect of heuristic biases on their perceived profitability. The third objective is to examine the effect of prospect theory-based biases on their perceived profitability.

The study is useful for academics, since it adds new knowledge to behavioral finance in a developing country. It is also useful for traders, financial educators, and regulators, since the findings can help them build better tools, lessons, and rules for a market that is fast-growing but still not regulated.

3. THEORY

This study uses behavioral finance as its main theory. Behavioral finance says that investors do not always act in a rational way. Their thinking shortcuts and their feelings can change their choices (Gunasena et al., 2024). The study looks at three groups of biases, and each group is described below.

Herding behavior. Herding theory says that people tend to follow the actions of others instead of using their own judgment, especially when the market is uncertain (Gunasena et al., 2024). In cryptocurrency trading, herding can lead traders to buy or sell at the wrong time only because other traders do the same. Roza et al. (2024) explain that social media plays a big part in herding, since traders often follow influencers and online trading groups. Gunasena et al. (2024) found that herding did not have a significant effect on the investment decisions of general Sri Lankan cryptocurrency investors, and they explained this by the small size of the market and the unclear rules in Sri Lanka.

Heuristic biases. Heuristic biases are mental shortcuts that people use to make fast decisions when they do not have full information. Gunasena et al. (2024)

study five heuristic biases: overconfidence, anchoring, availability bias, representativeness, and the gambler's fallacy. Overconfidence makes a trader believe that he or she is better than the average trader. Anchoring makes a trader depend too much on one reference price. Availability bias makes a trader depend on information that is easy to remember. Roza et al. (2024) argue that these biases are very risky for day traders, since day trading needs fast decisions in a market that changes very quickly.

Prospect theory-based biases. Prospect theory, developed by Kahneman and Tversky (1979), explains that people feel the pain of a loss more strongly than the pleasure of an equal gain. Gunasena et al. (2024) study three biases that come from this theory: loss aversion, regret aversion, and mental accounting. Loss aversion can make a trader hold on to a losing position for too long, hoping that the price will recover. Regret aversion makes a trader avoid decisions that may cause regret later. Mental accounting makes a trader treat money differently depending on where it came from. Roza et al. (2024) report that loss chasing and a false sense of control are important risk factors for cryptocurrency day traders.

Hypotheses. The dependent variable of this study is perceived profitability. It is the trader's own opinion of how profitable his or her trading is, and it is not the real profit from trading accounts. Earlier work shows that these biases are risky for day traders (Roza et al., 2024). However, traders who follow the crowd, trust their own mental shortcuts, or react strongly to gains and losses may feel more sure about their results, and they may rate their own trading higher. For this reason, the study expects a positive effect from each bias on perceived profitability. Based on this, the following hypotheses are proposed:

H1: Herding behavior has a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka.

H2: Heuristic biases have a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka.

H3: Prospect theory-based biases have a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka.

4. METHODS

This study follows a positivist research philosophy, since it measures the relationship between variables using numbers and statistical tests (Gunasena et al., 2024). A deductive approach is used, since the study starts with existing theory and tests specific hypotheses using collected data. A quantitative research strategy is used, since the study collects numerical data through a

questionnaire survey. A cross-sectional time horizon is used, since the study collected data at one point in time.

The target population of this study is active cryptocurrency day traders in Sri Lanka. A day trader is a person who buys and sells cryptocurrency within the same trading day (Roza et al., 2024). Cryptocurrency is not officially regulated in Sri Lanka, so there is no official list of traders, and the exact number of day traders is not known (Manoj, 2023). For this reason, the study could not use a sampling frame, and it could not select respondents by chance. It used non-probability sampling. The link to the questionnaire was shared in cryptocurrency day trading groups and communities on social media, and traders in these groups chose to answer it (convenience sampling). Only people who said that they were active day traders could answer. The number of responses was also watched so that three groups of trading experience were included: less than one year, one to three years, and more than three years (quota sampling). This was done because earlier studies show that trading experience affects trading behavior and profitability (Gunasena et al., 2024; Abarquez et al., 2025). Because of this sampling method, the results apply to the traders who answered the survey, and they cannot be generalized to all day traders in Sri Lanka.

The study received 511 responses. Eleven responses were removed because they were incomplete, were duplicates, or did not pass the day trader screening questions, so 500 valid responses were kept. An estimate shows about 410,000 cryptocurrency owners in Sri Lanka (Triple-A, 2024), but the number of day traders is not known. For a population of this size, Krejcie and Morgan (1970) give a sample size of 384. The sample of 500 is larger than this number. The model also has only three predictor constructs, and a sample of 500 is large for a model of this size.

Data were collected using a structured, self-administered questionnaire. The questionnaire has four sections. The first section asks about the trader profile, such as age, gender, education, income, trading experience, and platform. The other sections measure herding behavior (five items), heuristic biases (10 items), prospect theory-based biases (six items), and perceived profitability (seven items). All items were measured on a five-point Likert scale, from strongly disagree to strongly agree. The items for the three biases were adapted from Gunasena et al. (2024). The items for perceived profitability were adapted from Abarquez et al. (2025) and Gunasena et al. (2024). They cover total investment, total gains, return on investment, consistency of returns, overall performance, ability to cover losses, and satisfaction with trading outcomes. Perceived profitability was measured by the traders' own ratings, and it was not checked against trading account records. A pilot test with 10 respondents checked the clarity and the validity of the questionnaire.

Herding behavior was a first-order reflective construct with five items. Heuristic biases and prospect theory-based biases were second-order constructs, built with a two-stage approach. First, scores were computed for the lower-order constructs: overconfidence, anchoring, availability bias, representativeness, and the gambler's fallacy for heuristic biases, and loss aversion, regret aversion, and mental accounting for prospect theory-based biases. Then these scores were used as indicators of the higher-order construct. This approach was used because an early model, with all 10 and all six items as direct indicators, gave low average variance extracted (AVE) values of 0.283 for heuristic biases and 0.247 for prospect theory-based biases. The same early model gave an AVE of 0.247 for perceived profitability, so the three items with the lowest loadings were removed, and four of the seven items were kept. Perceived profitability shows how a trader rates his or her own trading results. A higher score on each construct means a higher level of that bias or a higher self-rating.

Data were analyzed in two steps. First, descriptive statistics (frequency, mean, and standard deviation) were used to summarize the demographic profile of the respondents and the general pattern of answers. Second, the three hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, since this method works well with small to medium sample sizes and does not need normally distributed data (Hair et al., 2019). The measurement model was checked first, using indicator loadings, Cronbach's alpha, composite reliability (CR), AVE, the Fornell-Larcker criterion (Fornell & Larcker, 1981), and the heterotrait-monotrait (HTMT) ratio. The structural model was checked next, using full collinearity variance inflation factor (VIF) values (Kock, 2015), path coefficients, *t*-values, *p*-values, the coefficient of determination (R^2), adjusted R^2, effect size (f^2), and predictive relevance (Q^2). The full collinearity VIF test was also used to check common method bias, and Harman's single-factor test was used as a second check. The significance of the paths was tested using bootstrapping with a two-tailed test at the 5 percent level, so a *t*-value above 1.96 means a significant path.

5. RESULTS

Out of 511 responses received, 500 were valid and complete, which gives a response rate of 97.8 percent. Four respondents (0.8 percent) gave the same answer to all items. They were kept in the data, because the reliability results changed very little when they were removed. Table 1 shows the sample profile. Most respondents were male (71 percent) and aged between 26 and 35 years (67 percent). The largest group held a General Certificate of Education

(G.C.E.) Advanced Level (43 percent), and most worked part-time (43 percent) or full-time (37 percent).

Table 1: Sample Profile of Respondents

Characteristic	Most Common Group	Respondents (%)
Gender	Male	71
Age	26 to 35 years	67
Education	G.C.E. Advanced Level	43
Employment	Part-time work	43
Monthly income from trading	LKR 50,001 to 100,000	60
Trading experience	One to three years	61.8
Main platform	Binance Futures	58
Trades per day	Four to six trades	57

Note. N = 500. LKR = Sri Lankan rupee; G.C.E. = General Certificate of Education.

Most traders earned between 50,001 and 100,000 Sri Lankan rupees (LKR) per month from cryptocurrency trading (60 percent). By trading experience, 35.4 percent had less than one year, 61.8 percent had one to three years, and 2.8 percent (14 traders) had more than three years. Binance Futures was the main platform for 58 percent of the traders, and Bybit for 39 percent. Most traders (57 percent) made four to six trades a day, and another 40 percent made one to three trades a day. This profile matches the young, active day trader population that this study aims to examine.

Table 2: Reliability and Convergent Validity

Construct	Indicators	Loadings	Cronbach's Alpha	CR	AVE
Herding behavior	Five items	0.795 / 0.709 / 0.700 / 0.649 / 0.741	0.767	0.843	0.519
Heuristic biases	Five lower-order scores	0.715 / 0.757 / 0.740 / 0.774 / 0.765	0.805	0.866	0.563
Prospect theory-based biases	Three lower-order scores	0.755 / 0.741 / 0.734	0.594	0.787	0.553
Perceived profitability	Four items	0.677–0.734	0.681	0.807	0.511

Note. CR = composite reliability; AVE = average variance extracted. For the two second-order constructs, the loadings are those of the lower-order construct scores.

The mean scores of all four constructs were above 4.0 on the five-point scale (from 4.15 to 4.38), so most traders agreed with the statements.

Table 2 shows the reliability and validity results. All indicator loadings were above 0.60. CR values ranged from 0.787 to 0.866, and all AVE values were above 0.50. Cronbach's alpha was 0.594 for prospect theory-based biases and 0.681 for perceived profitability, which is below the usual limit of 0.70. These two constructs have few indicators, and alpha is a strict measure for such constructs, so CR was used as the main reliability measure (Hair et al., 2019). The Fornell-Larcker criterion was met for all pairs of constructs (Fornell & Larcker, 1981).

Table 3 shows the HTMT values. One pair, heuristic biases and prospect theory-based biases, had an HTMT value of 0.919, which is above the strict limit of 0.90 that is often used. The other five pairs were below 0.85 (from 0.329 to 0.470). This study did not compute bootstrap confidence intervals for the HTMT values, so the overlap of these two constructs could not be tested further.

Table 3: HTMT Values

Pair of Constructs	HTMT
Herding behavior – Heuristic biases	0.431
Herding behavior – Prospect theory-based biases	0.329
Herding behavior – Perceived profitability	0.406
Heuristic biases – Prospect theory-based biases	0.919
Heuristic biases – Perceived profitability	0.430
Prospect theory-based biases – Perceived profitability	0.470

Note. HTMT = heterotrait-monotrait ratio.

Table 4 shows the path coefficients, *t*-values, *p*-values, and effect sizes for the three hypotheses. Herding behavior had the strongest effect on perceived profitability, followed by prospect theory-based biases, and then heuristic biases. All three hypotheses were supported. The three biases together explained 14.9 percent of the variance in perceived profitability ($R^2 = 0.149$; adjusted $R^2 = 0.144$). The predictive relevance was small but above zero ($Q^2 = 0.122$; Hair et al., 2019). The f^2 value was 0.038 for herding behavior, which is a small effect. The values for heuristic biases (0.015) and prospect theory-based biases (0.019) are just below the 0.02 limit for a small effect (Cohen, 1988). Full collinearity VIF values ranged from 1.173 to 1.840, which is well under the threshold of 3.3 (Kock, 2015).

Table 4: Path Coefficients and Hypothesis Tests

Hypothesis	β	*t*-value	*p*-value	f^2	Decision
H1: Herding behavior - Perceived profitability	0.190	4.345	0.000	0.038	Supported
H2: Heuristic biases - Perceived profitability	0.142	2.682	0.008	0.015	Supported
H3: Prospect theory-based biases - Perceived profitability	0.157	3.040	0.002	0.019	Supported

Note. β = path coefficient. The dependent variable is perceived profitability.

6. DISCUSSION

This study tested whether herding behavior, heuristic biases, and prospect theory-based biases have a positive effect on the perceived profitability of cryptocurrency day traders in Sri Lanka. The results support all three hypotheses. An important point is that profitability in this study is based on the traders' own opinion about their performance, not on checked numbers from real trading accounts. A positive path therefore means that traders with stronger biases also rate their own trading as more profitable. It does not mean that these biases create higher real profit. One possible reason for this pattern is that biased traders feel more sure about their trades, and they may judge their own results in a better way. This reason was not tested in this study.

The difference between perceived profit and real profit matters. A trader may feel profitable because of a few recent wins, or because the trader compares his or her results with only a few other traders. A trader may also forget past losses. In all these cases, the self-rating can be higher than the real result. Without data from real trading accounts, this study cannot say how large the gap is.

The finding that herding behavior has the strongest effect on perceived profitability is different from Gunasena et al. (2024), who found that herding did not significantly affect general investment decisions in Sri Lanka. The two studies used different samples and different outcome variables, so the results cannot be compared directly. Gunasena et al. (2024) explain their result by the small size of the Sri Lankan market and the unclear rules. A possible reason for the difference is that day traders have very little time to decide, so following other traders becomes a fast and easy way to decide, especially in a market that runs for 24 hours and is strongly shaped by social media (Roza et al., 2024).

The finding on heuristic biases agrees with Gunasena et al. (2024), who also found that heuristic biases significantly affect the decisions of cryptocurrency traders in Sri Lanka. The finding on prospect theory-based biases is in line with Roza et al. (2024), who found that loss chasing and a false sense of control are important risk factors for cryptocurrency day traders. However, Roza et al. (2024) describe these factors as risk factors, while this study links the biases to perceived profitability. Traders who show these biases may not see the risk in their own behavior. This is a possible reason only, and it needs more testing with real trading data.

The explanatory power of the model is low ($R^2 = 0.149$). The three biases explain 14.9 percent of the variance in perceived profitability, so 85.1 percent is explained by other factors. This shows that behavioral biases are only part of the story. Other factors outside this study, such as market conditions, the amount of capital used, and risk management skills, may also play an important role in shaping profitability. The path coefficients are between 0.142 and 0.190, which are low in size, and the effect sizes are very small (f^2 from 0.015 to 0.038). The predictive relevance is also small ($Q^2 = 0.122$). The effects are statistically significant, but their practical size is small, and they should not be read as strong drivers of trader profitability. The mean scores of all constructs were above 4.0 with little spread, so most traders gave high ratings. This may reduce the differences between traders and make the relationships weaker.

The HTMT value of 0.919 between heuristic biases and prospect theory-based biases shows that these two constructs overlap. The Fornell-Larcker criterion was met for all pairs of constructs, but HTMT is a stricter test. Heuristic biases are mainly thinking shortcuts, and prospect theory-based biases are mainly emotional reactions to gains and losses. One possible reason for the overlap is that, in day trading, a trader's fast thinking mistakes and emotional reactions to loss often happen together in the same decision, rather than as two separate steps. This reason is an explanation only, and this study did not test it with statistical analysis. Because of the overlap, the result that the three biases have separate effects should be read with care. The effects of heuristic biases and prospect theory-based biases may not be fully separate from each other. This is a limitation of the study. Future studies can test the two constructs again, and they can merge or revise them if the overlap remains.

These findings apply to the 500 traders in this sample. Because the sample came from social media groups, traders who are active in these groups may be different from traders who are not. The group with more than three years of experience was also small (14 traders), so the results mainly describe traders with up to three years of experience. The findings should therefore be used as a first step, and they should be tested again with other samples.

7. IMPLICATIONS AND LIMITATIONS

For theory, this study adds new knowledge to behavioral finance in a developing country. It shows that, among the traders who answered the survey, herding behavior, heuristic biases, and prospect theory-based biases are all linked with higher perceived profitability. The study also shows that a measure based on self-rating can be different from real profit, so future studies should keep these two ideas apart. The result for herding is different from an earlier study of general investors in Sri Lanka, which suggests that the effect of a bias may depend on the type of trader.

For traders, the findings suggest that feeling profitable is not the same as being profitable. Traders are encouraged to build a clear trading plan with a fixed entry point, exit point, and stop-loss point before they start trading, and to keep a trading journal to track their real results over time. Traders should also base their decisions on checked market information rather than social media trends, and they should spread their trading across different assets instead of risking everything on one position.

For trading platforms, the findings suggest three steps. Platforms are encouraged to add risk warning messages for impulsive or repeated trading, to provide simple educational tools about behavioral biases, and to build performance dashboards that show traders their real trading numbers next to their own self-rating. This is useful because traders with stronger biases rated their own trading as more profitable in this study. Financial regulators and educational bodies are encouraged to run financial literacy and public awareness programs about herding and emotional trading, since cryptocurrency remains an unregulated market in Sri Lanka.

This study has seven limitations. First, profitability was self-reported, so the study cannot say anything about real profit. Second, the study used non-probability sampling in social media groups, so the sample may not represent all day traders in Sri Lanka, and the group with more than three years of experience was small (14 traders, 2.8 percent). Third, the design was cross-sectional, so the study shows links between variables and does not prove cause and effect. Fourth, the HTMT value between heuristic biases and prospect theory-based biases was 0.919, so these two constructs overlap, and the study did not compute confidence intervals for the HTMT values. Fifth, the model explains only 14.9 percent of the variance in perceived profitability. Sixth, all variables came from one self-reported survey, so common method bias and answers that seem more acceptable to the trader are possible. Harman's single-factor test and the full collinearity VIF test did not show a serious problem (all VIF values were below 3.3; Kock, 2015), but these tests cannot remove this risk fully. Seventh, most respondents used Binance Futures (58 percent) or

Bybit (39 percent) as their main platform, and all respondents were traders in Sri Lanka, so the findings may not apply to traders on other platforms or in other countries.

Future research should use real trading account data, follow traders over a longer period, include traders from other platforms and countries, and use probability sampling if a sampling frame becomes available. It should also test the two overlapping constructs again, and it can combine them into one construct if the overlap remains. It should add other factors such as market conditions, the amount of capital used, risk management skills, and financial education.

In conclusion, this study examined how herding behavior, heuristic biases, and prospect theory-based biases affect the perceived profitability of cryptocurrency day traders in Sri Lanka. Using data from 500 active day traders and PLS-SEM analysis, the study found that all three biases have a positive and significant effect on perceived profitability, and herding behavior has the strongest effect. The results do not show that biases improve real profit. They show that traders with stronger biases rate their own trading results higher. The model explains only a small part of perceived profitability, so the results should be read with care.

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