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Impact of Behavioural Biases on Cryptocurrency Investment Decisions with the Moderating Effect of Financial Literacy

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Abstract

Cryptocurrency investments have gained global popularity in the recent past. In the volatile markets, behavioural biases can lead to suboptimal investment decisions. Lack of financial literacy further intensifies behavioural biases, leading to emotional and irrational investment decisions. This study investigates the impact of herding, heuristics, and prospect factors on cryptocurrency investment decisions in Sri Lanka, with a focus on the moderating role of financial literacy. A quantitative research design was employed, collecting data from 158 cryptocurrency investors through self-completion questionnaires distributed via social media platforms. Descriptive and inferential statistics were used to analyse the data, and Partial Least Squares-based Structural Equation Modeling (PLS-SEM) was applied to measure the influence of the identified biases on investment decisions. The results indicate that heuristic and prospect factors have a greater influence on investment decisions compared to the herding effect. Additionally, financial literacy does not moderate the impact of these biases on investment decisions. These findings contribute to literature while providing insights for investor education and guiding policymakers in regulating informed investment decisions to reduce impulsive, bias-driven choices.

Keywords: Cryptocurrency investments, Behavioural biases, Herding, Heuristics, Prospect factors, Financial literacy

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Introduction

Cryptocurrencies, exemplified by Bitcoin's inception in 2009, represent a significant financial innovation through blockchain technology (Joo et al., 2020). These digital currencies operate in decentralised, encrypted, and digitised ways, differing fundamentally from centrally regulated traditional currencies (Kim, 2022). The rise of the cryptocurrency market and the development of investment platforms have created investment opportunities for individuals. As illustrated in Figure 1, the cryptocurrency market comprises over 22,000 digital assets with a global market capitalisation of $1.42 trillion as of November 2023 (CoinMarketCap, n.d.). The market has seen significant growth, particularly in 2017 and 2023, though it has also faced declines, underscoring the importance of analysing market trends (Kucharova et al., 2021).

Figure 1

Global Cryptocurrency Market Capitalisation

Source: Coin Market Capitalisation, 2023

The increasing interest in cryptocurrency investments is to be attributed to the potential financial gains that individuals intend to achieve (Bouri et al., 2017). Similar to the global market, the Sri Lankan crypto market is also being identified as the fastest-growing monetary network. After covid-19 pandemic, the Sri Lankan economy has undergone significant economic challenges and consequently, investors have identified the potential in cryptocurrency markets when looking for alternative investment options (Dharmasiri, 2023). Director of ‘Paxful’, a leading P2P crypto trading platform stated that with the depreciation of the Sri Lankan rupee during the economic recession, there was a 730 % growth in the Sri Lankan crypto traders (Sewmini, 2023). This trend highlights the need to delve into the behavioural factors that influence investment decisions in this emerging market.

Cryptocurrency has not yet been legalised in Sri Lanka. The Central Bank of Sri Lanka has issued multiple warnings regarding cryptocurrency activities, describing them as unregulated investment instruments lacking legal recognition or regulatory protections

(Central Bank of Sri Lanka, 2023). Despite the regulatory challenges, there is a growing interest among individual investors in Sri Lanka regarding cryptocurrency investments. According to the 2023 Global Crypto Adoption Index, Central and Southern Asia has been reported at the forefront of cryptocurrency adoption. Accordingly, India, Vietnam, Indonesia, Pakistan, and Thailand were among the top 10 countries for cryptocurrency adoption where Sri Lanka has been ranked at 49 in 2023 and 58 in 2022 (Chainalysis Adoption Index, 2023). Hence, there is a positive trend in cryptocurrency investments in Sri Lanka, but still a bit lagging behind other Asian countries.

Cryptocurrency differs significantly from traditional assets due to its unique characteristics, high volatility and lack of regulation which necessitate the need for research on how investors' behavioral biases impact their decision-making (De Silva et al., 2021). Further, in recent years, there have been several fluctuations in the cryptocurrency market, and many investors have accused the big investors of manipulating the market (Eigelshoven et al., 2021). Numerous studies have been conducted investigating the impact of behavioural biases on stock market decision-making (Cao et al., 2021; Rehan et al., 2021; Wijaya & Zunairoh, 2021). However, there is a notable gap concerning how behavioural biases influence cryptocurrency investments, especially in emerging markets like Sri Lanka with the level of financial literacy of Sri Lankan investors (Sachitra & Rajapaksha, 2023). Hence, a comprehensive assessment of an investor is essential for guidance in making a more beneficial investment decision.

The study of behavioural finance reveals the significant impact of investors' behaviour on the economic ecosystem. Investors' investing decisions are influenced by a variety of behavioural finance factors, such as the herding effect, heuristic factor, and prospect factor (Das et al., 2022). Boxer and Thompson (2020) stated that herd behaviour is a social phenomenon when individuals in a group prefer following the behaviour or actions of the larger group rather than making their own judgments. According to Sherani and Naveed (2022), a heuristic factor refers to a fundamental belief or a rule of thumb used to address issues, make decisions, or make judgments. It's a mental shortcut that helps people resolve problems and make decisions quickly with limited knowledge or resources. Said et al. (2020) stated that the prospect theory, developed by Kahneman and Tversky in 1979, is also one of the behavioural economic theories that help analyse how individuals make their decisions under risk and uncertainty.

According to the researcher, few studies have investigated how behavioural aspects affect investment decisions on cryptocurrency. Even in Sri Lanka, where studies are limited, there has not been much focus on the behavioural aspects of cryptocurrency investors' decisions (Sachitra & Rajapaksha, 2023). Numerous studies have shown that herding, heuristics, and prospect factors have a positive impact on individual investors' stock market decision-making (Cao et al., 2021; Rehan et al., 2021; Wijaya & Zunairoh,). Few studies have looked at how behavioural biases affect cryptocurrency investment decisions (Al-Mansour, 2020). Thus, the discussion on this topic remains ongoing. Investor actions influence crypto market patterns, which have economic consequences. It is essential to research both the psychological and behavioural characteristics of investors to comprehend how behavioural factors impact their decision-making (Al-Mansour, 2020). Many studies found that financial literacy significantly moderates the relationship between behavioural biases and investment decisions among stock market investors (Khan et al., 2023; Rahayu et al., 2022), while other studies have found no such relationship (Hildebrandus et al., 2015; Rahayu et al., 2022).

Financial literacy plays a crucial moderating role in the relationship between behavioural biases and investment decisions, enhancing rationality in investor behaviour. Studies like those by Abideen et al. (2023) demonstrate that financial literacy mitigates the effects of biases, leading to more informed and less emotionally-driven investment choices. Khan et al. (2023) found that in the Pakistan stock market, financial literacy moderates the impact of behavioural biases, such as overconfidence and herding, thereby promoting more rational investment decisions. Abideen et al. (2023) further support this by showing that financial literacy helps moderate various behavioural biases in investment contexts. Adil et al. (2022) underscore this point by illustrating how financial literacy specifically moderates overconfidence, herding, and risk-aversion biases, leading to more accurate investment behaviors. Despite the limited literature on the topic, Quddoos et al. (2020) acknowledge the significant role of financial literacy in tempering the influence of behavioral biases on investment decisions, highlighting its importance in fostering better financial outcomes. Thus, incorporating financial literacy as a moderating factor is justified as it enhances investor rationality and decision-making quality amidst behavioural biases. Through a critical literature review, researchers discovered that prior studies in the cryptocurrency domain had ignored the moderator effect of financial literacy on behavioral biases (Akuntansi et al., 2022; Al-Mansour, 2020; Sachitra & Rajapaksha, 2023).

Therefore, this paper has three main objectives: firstly, to examine the effects of herding on the cryptocurrency investment decisions of Sri Lankan individual investors; secondly, to analyse the influence of heuristic factors and prospect factors on the cryptocurrency investment decisions of Sri Lankan individual investors; finally, to analyse the moderating effect of financial literacy between behavioural biases (herding behaviour, heuristic decision-making, and prospect factors) and investment decisions on cryptocurrency by Sri Lankan individual investors. The remainder of this article is organised as follows: Section 2 outlines the literature, Section 3 presents the conceptual framework and Section 4 details the research methodology. The results are discussed in Section 5, while Section 6 covers conclusions, implications, limitations and suggestions for future research.

Literature Review

In investment decision-making, investors often take into consideration a variety of parameters, such as risk tolerance, potential returns, economic indicators, market situations, and their own financial goals (Lai, 2019). Behavioural finance explores how psychological biases impact financial decision-making, challenging the assumption of rationality and market efficiency (Shukla, 2020). Nakamoto (2008) claimed that cryptocurrencies operate through a distributed, decentralised, and peer-to-peer network. According to Dennis and Griffin (2018), there are no particular governing bodies in charge of approving and monitoring the transfers of assets inside the network. The lack of legal recognition and decentralised nature lead the way for behavioural biases in cryptocurrency investments. The studies reveal that ordinary investors make decisions depending on emotion instead of logic; many investors tend to buy when projections are high and sell when fear sets in, often at lower prices. Psychological research illustrates that the discomfort associated with losing money through investments is approximately three times greater than the happiness of gaining income. Emotions such as greed and fear usually play a significant part in investors' decisions (Tanvir et al., 2016).

Behavioural finance provides a framework for understanding how cognitive biases such as herding, heuristics, and the insights of Prospect theory impact decision-making under uncertainty (Al-Mansour, 2020; Das et al., 2022). Herding behaviour is a significant aspect of behavioural finance, where investors mimic the decisions of others rather than making independent choices (Ajaz & Kumar, 2018; Rosdiana, 2020). Ali (2022) mentioned that investors tend to conform to the crowd rather than make decisions independently. This behavior is more pronounced during panic periods, such as the COVID-19 pandemic, and during bullish market conditions. It has been noticed that participants in the Bitcoin marketplace work in herds and thus impact the crypto price (Peters, 2003). Gyamerah (2021) emphasised understanding herding behaviour is important for investors, regulators, and market participants to effectively navigate the cryptocurrency market.

According to Ritter (2003), heuristics are rules of thumb that simplify difficult decision-making processes by decreasing the amount of effort needed to anticipate values and assess likelihood. These heuristics are frequently highly beneficial, particularly in instances where time is of the utmost importance (Waweru et al., 2008). However, on occasion, they may create biases in cryptocurrency investment decisions. Tversky and Kahneman (1947) have identified three components of heuristics: anchoring, availability bias, and representativeness. Furthermore, Waweru et al. (2008) incorporated two elements into the heuristic framework: overconfidence and the gambler's fallacy. Sachitra and Rajapaksha (2023) have identified that heuristic-driven biases affect cryptocurrency adoption by Sri Lankan cryptocurrency investors. This study focuses on the representativeness, Gambler's Fallacy, Anchoring, overconfidence and availability biases under heuristic theory.

Prospect theory explains a variety of mental states that are likely to impact how individuals make decisions. The emotional impact of losses can significantly influence investment behaviours, resulting in suboptimal financial decisions (Said et al., 2020). The three basic concepts are loss aversion, regret aversion and mental accounting (Wijeya & Zunairoh, 2021) which are considered in this study under prospect theory. Particularly the investment decisions made in cryptocurrency are impacted by the emotional states due to its specific nature. Said et al. (2020) stated loss aversion frequently leads to poor decision-making and has a direct influence on investor wealth. According to Statman (1999), when people make an error in judgment, they typically suffer depression and regret. When evaluating whether to sell assets, investors tend to be affected emotionally by whether they paid more or less at the time of purchase. Therefore, this study aims to investigate how herding behaviour, heuristic decision-making, and prospect theory-related mental states influence the decisions made by cryptocurrency investors.

Financial literacy plays a vital role in finance decision making specifically when considering the digital currency investments. Stöckl et al. (2015) found that investors with a lack of financial knowledge are less inclined to invest in high-risk assets or seek professional assistance. Morgan and Trinh (2020) discovered that financial literacy positively impacts financial inclusion. Financial literacy enables informed decisions and reduces financial issues. A study by Wijaya et al. (2023) considered financial literacy as a moderating factor and analyzed the correlation between stock investing decisions and the heuristic and herding factors. Morgan and Trinh (2020) demonstrated the significance of having a high-level financial understanding to make wise investment decisions for better financial well-being for people, companies, and actual investors. Hence, this study will investigate the moderating effect of financial literacy on the impact of behavioural biases on cryptocurrency investments.

Hypotheses

Most of the researchers' biases in judgments were greatly impacted by herding habits, and this in turn impacted their equity market investing decisions. A parallel investigation conducted by Almansour et al. (2023) revealed that both herding behavior and heuristics significantly impact the investment choices made by investors in the Gulf region within the cryptocurrency market. Furthermore, many other studies also highlighted the herding effect influences the process of decision-making among investors (Ali, 2022; Al Mansour, 2020; Rahyuda & Candradewi, 2023). Based on the literature the first hypothesis was developed as,

H_1: Herding factors have a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.

A study conducted by Piotrowski and Bünnings (2022) discovered that heuristics influenced the likelihood of customers purchasing securities. Additionally, Gitau et al. (2018) discovered that heuristic factors have a significant connection with real estate investment. Further, Juwita et al. (2022) researched to understand how millennials and Gen Z in Indonesia make investment decisions by analysing the role of behavioural finance characteristics such as herding, heuristics, and prospects. Loris and Jayanto (2021) conducted a study examining the factors influencing investment decisions among Sharia investors, finding that representativeness, risk perception, anchoring, and herding positively impact their investment choices. Accordingly, the second hypothesis of the study is,

H_2: Heuristic factors have a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.

Representativeness bias has been shown to have a significant impact on investment decisions, as evidenced by multiple research studies (Ramalakshmi et al., 2019; Xia, 2023). The findings underscore the significant role of representativeness bias in shaping investment decisions and emphasise the importance of awareness and measures to counteract its effects. Thus, the next hypothesis posits this relationship,

$H_{2a:}$ Representative bias has a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.

Anchoring bias has been identified as a significant factor influencing investment decisions in various studies. The findings of the studies collectively suggest that anchoring bias plays a substantial role in influencing investment decisions, underscoring the importance of understanding and mitigating cognitive biases in the investment process (Boemiya et al., 2023; Kartini & Nahda, 2021; Ramalakshmi et al., 2019). Accordingly, the next hypothesis of the study is,

> *H_{2b}: Anchoring bias has a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.*

Overconfidence bias has been identified having a substantial influence on investment decisions, particularly in the context of cryptocurrency investments (Hafishina et al., 2023; Syarkani & Tristanto, 2022). According to Hafishina et al. (2023), overconfidence bias is a significant factor influencing cryptocurrency investment decisions, as highlighted in the study. Additionally, Syarkani and Tristanto (2022) in Indonesia, individual student investors' cryptocurrency investment decisions are significantly influenced by overconfidence bias. Therefore, the next hypothesis of the study is:

> *H_{2c}: Overconfidence bias has a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.*

Research findings have indicated that the gambler's fallacy, along with other biases like overconfidence and loss aversion, can impact investment decision-making both individually and collectively (Mahadwartha et al., 2023; Rahman & Dewi, 2023; Stöckl et al., 2015). The gambler's fallacy bias, along with other behavioural biases like overconfidence, herding, and anchoring, significantly influences cryptocurrency investment decisions (Hidajat, 2019). Hence, the study formulates the next hypothesis of the study as,

> *H_{2d}: Gambler's fallacy bias has a significant influence on cryptocurrency investment decisions of Sri Lankan individual investors.*

The ease of obtaining information due to availability bias can lead investors to make decisions based on quickly accessible data, impacting their investment choices and potentially leading to suboptimal outcomes (Mahadwartha, 2023). Research has indicated that availability bias, along with other behavioral biases like overconfidence, herding, and anchoring, plays a crucial role in shaping investors' decision-making processes in the cryptocurrency market (Ayundha et al., 2023; Hafishina et al., 2023). Therefore, the next hypothesis of the study is,

> *H_{2e}: Availability bias has a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.*

A study conducted by Rahawarin (2023) on the influence of loss aversion and regret aversion biases on decision-making among SMEs shows that both biases affect investing decisions and that the relationship between the two is mediated by financial literacy. A study conducted by Alaaraj and Bakri (2020) explored the relationship between organisational performance and two psychological biases: loss aversion and mental accounting. This research found psychological biases (prospect factors) in decision-making processes among investors and managers. Accordingly, the third hypothesis of the study is,

H_3: Prospect factors have a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.

Loss-aversion bias does have a significant influence on cryptocurrency investment decisions, as indicated by research findings (Almansour et al., 2023). These findings collectively suggest that loss aversion bias significantly affects how investors engage with cryptocurrencies, contributing to the complexities of their investment behavior and decision-making processes. Therefore, the next hypothesis of the study is,

H_{3a}: Loss aversion bias has a significant influence on cryptocurrency investment decisions of Sri Lankan individual investors.

As per the research findings of the study conducted by Nursalimah et al. (2022), regret-aversion bias does have a significant influence on cryptocurrency investment decisions. Similarly, research in Indonesia suggests that regret aversion bias affects investment decisions among millennials, although financial literacy may not have a direct impact (Qazi et al., 2023). Thus, the next hypothesis of the study is formulated as,

H_{3b}: Regret aversion bias has a significant influence on cryptocurrency investment decisions of Sri Lankan individual investors.

Mental accounting bias does have a significant influence on investment decisions, as evidenced by various studies (Ginting et al., 2023; Ramalakshmi et al., 2019; Rana, 2023). These findings collectively suggest that mental accounting bias plays a crucial role in shaping investment decisions and should be considered by investors when making financial choices. Hence, the next hypothesis of the study is,

H_{3c}: Mental accounting bias has a significant influence on the cryptocurrency investment decisions of Sri Lankan individual investors.

Agnew and Harrison (2015) pointed out that investors must possess strong financial literacy to make well-informed judgments free of emotional bias. Pratiwi and Puspawati (2022) found similar outcomes, indicating that the association between equity market participation and investment decisions is moderated by an individual's financial literacy level. Ramalakshmi et al. (2019) demonstrated that the degree of financial literacy of a person influences the relation of risk tolerance to investing decisions. Thus, the next couple of hypotheses if the study investigates,

H_4: Financial literacy moderates the relationship between herding factors and cryptocurrency investment decisions of Sri Lankan individual investors.

H_5: Financial literacy moderates the relationship between heuristics factors and cryptocurrency investment decisions of Sri Lankan individual investors.

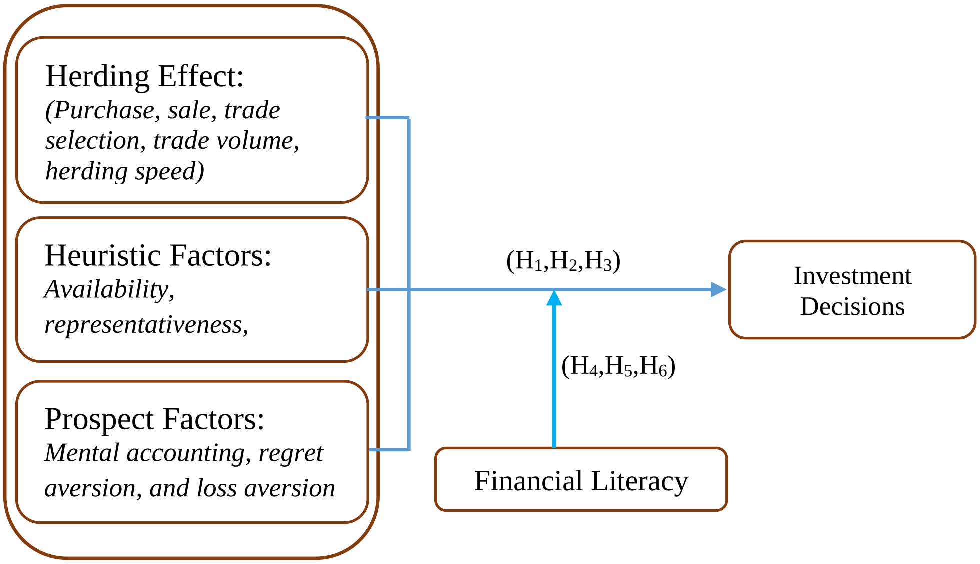
H_6: Financial literacy moderates the relationship between prospective factors and cryptocurrency investment decisions of Sri Lankan individual investors.

Conceptual Framework

This research investigates how herding behaviour, heuristic decision-making, and prospect theory influence cryptocurrency investment decisions in Sri Lanka. The dependent variable is the investment decision, influenced by these behavioural factors; herding effect, heuristic factors and prospect factors as independent variables (Cao et al., 2021; Mahmood et al., 2016 Rehan et al., 2021; Wijaya & Zunairoh, 2021). The study also explores financial literacy as a moderating factor, incorporating the insights from the studies conducted by Al Mansour (2020) and Akuntansi et al. (2022) and adapting the framework established by Mahmood et al. (2020).

Figure 2

Conceptual Framework



Operationalisation

The questionnaire has been developed after carefully studying the literature relating to similar kinds of studies. making some adjustments to align them with the objective of this study, the questionnaire consists of four sections. According to the literature review, particularly studies by Al-Mansour (2020) and Akuntansi et al. (2022) and, three primary variables, namely herding, heuristics, and prospect, have been identified to measure behavioural biases. The first section of the questionnaire focuses on determining whether respondents have invested in cryptocurrency and collects information about their demographics, such as age, gender, marital status, level of education, and income.

The following three sections (second to fourth) include a total of 36 questions. To assess investor behavioral biases, 20 measurement items were included that addressed herding, heuristic, and prospect biases. Herding Effect (HER), Overconfidence (OC), Anchoring (AN), Gambler's fallacy (GF), Ability bias (AV), Loss Aversion (LA), Regret Aversion (RA) and mental accounting have been used as sub-behavioural biases. These measurement items were developed based on the studies conducted by Wijaya and Zunairoh (2021), Al Mansour (2020), Rehan et al. (2021), Cao et al. (2021), Mahmood et al. (2016). Ahmed et al. (2022).

Financial literacy is considered a moderating variable, and it is measured using nine questions adapted from Potrich et al. (2020) under Financial Knowledge (FK), Financial Attitude (FA), and Financial Behaviour (FB). Lastly, the measurement of investment (INV) decisions involves seven questions taken from the study conducted by Ogunlusi and Obademis (2021). The necessary adjustments to the copied measurement items from previous literature have been made to align them with the objective of this study. A five-point Likert scale is utilised as the measurement tool for assessing herding, heuristics, prospect factors, and investment decisions. Additionally, a combined Likert scale or short scale is utilised as the measurement tool for evaluating financial literacy.

Research Methodology

Research Strategy

In this study, the objective is to analyse how herding behaviour, heuristics, and prospect factors influence the decision-making processes of cryptocurrency investors. Therefore, the study follows a positivist research philosophy, adopting a deductive approach. For this study, a quantitative research methodology has been utilised. Quantitative research is commonly associated with a deductive approach (Brown et al., 2019), which aligns with the chosen research approach in this study.

Population, Sampling Technique and Sample

The study targeted cryptocurrency investors in Sri Lanka as the population of the study. A sample of 500 cryptocurrency investors, yielded 158 responses, a response rate of 32%. Previous studies conducted by Al Mansour (2020), Akuntansi et al. (2022), and Wijaya et al. (2023) have used sample sizes of 112, 140, and 118. Hence, the sample size is justifiable for this study. Purposive sampling was used to gather responses from social media groups dedicated to cryptocurrency education and trading. This is particularly useful when the research aims to study a particular group or phenomenon, and participants need to possess certain characteristics or experiences (Isaac, 2023).

Data Collection

Among the several techniques for gathering data, the method chosen for this study to gather data is the self-completion approach. This method is commonly used in research because it allows for the distribution of several questionnaires at once. The self-completion questionnaire is preferred because it gives respondents the flexibility to complete it whenever they find it convenient. This ensures their comfort while providing their responses (Le Luong & Ha, 2011). The questionnaire has been specifically designed in English. It is assumed that all respondents, who are cryptocurrency investors based in Sri Lanka, have an understanding of English since they use it regularly in their work and daily lives. The questionnaire starts with an introduction that provides context for the respondents. The researcher used Google Forms-type and distributed it among the members of professional cryptocurrency trading social media groups on WhatsApp, Facebook and Telegram Messenger.

Pilot Survey

A pilot survey was carried out, involving two participants from each category: university lecturers, cryptocurrency traders, undergraduate students, master's degree students, and individuals who plan to invest in cryptocurrency in the future. Our objective was to assess factors such as language usage, questionnaire completion ease, and question relevance in measuring the intended items. We received feedback regarding question clarity, wording, interpretation, and appropriateness. Based on the insights gathered from the pilot test, we made revisions to the original questionnaire. These adjustments involved rephrasing items and eliminating others that were considered irrelevant or ineffective.

Data Analysis

Data analysis was conducted in two stages. First, descriptive statistical methods were applied to comprehend the dataset. Exploratory factor analysis was conducted afterwards using SMART PLS 4 software to evaluate construct validity and reliability. Following this, inferential statistical techniques, particularly structural equation modeling (SEM), were used to validate the conceptual model and the proposed relationships (Cao et al., 2021; Luong & Ha, 2011; Sorongan, 2021).

The decision to use SMART PLS (Partial Least Squares) is based on several methodological considerations. Firstly, SMART PLS is less stringent in terms of data distribution assumptions, making it more robust to deviations from normality. This is advantageous when dealing with complex models and non-normal data, which is common in behavioral finance research (Hair et al., 2017). Secondly, given that the study aims to explore new relationships and moderating effects, SMART PLS is more suitable as it is designed for exploratory research and theory development, (Hair et al., 2017). Thirdly, SMART PLS can handle complex models with many constructs and indicators more efficiently, especially with smaller sample sizes. The sample size of the study is 158 is more appropriate for PLS-SEM, known for its ability to provide reliable results with smaller samples (Henseler et al., 2009).

Lastly, SMART PLS is particularly focused on maximizing the predictive accuracy of the model, which is a key goal of this research (Hair et al., 2019).

Results and Discussion

Reliability and Validity of the Constructs

The study confirms strong internal consistency and reliability among its constructs, meeting established criteria outlined by Hair et al. (2019). Specifically, variables AN, AV, FB, FK, GF, HER, INVD, LA, MA, OC, RA, and REP exhibit Cronbach's alpha values above 0.60, composite reliability values exceeding 0.70. Average variance extracted (AVE) values equal to or greater than 0.50, demonstrating robust convergent validity as per Sekaran and Bougie (2009). The corresponding square root of AVE in each construct of this study is greater than its connection with other components. Additionally, the HTMT values of the study are all below 0.90, signifying no concerns regarding discriminant validity.

Test of Linearity and Normality of the Data

According to the results of the SPSS data analysis, data for each of the variables is not regularly distributed. Hence, the partial least squares (PLS) method was used (Hair et al., 2019).

Composition of the Sample

The demographic profile of the respondents is summarized according to the respondent characteristics. The survey of cryptocurrency investors in Sri Lanka reveals a significant gender gap, with 81.65% male and 18.35% female participants. The age distribution shows that 50.63% are between 25 and 35 years old, while 37.34% are between 36 and 45 years old. Education levels are diverse, with 32.91% holding bachelor's degrees, 22.78% holding diplomas, and 19.62% holding master's degrees. Income levels vary, with 29.11% earning Rs. 100,001–150,000 monthly. Most investors are married (55.06%) and work in the private sector (47.47%). In terms of cryptocurrency trading education, 39.87% have completed a trading course. The majority (93.04%) use the Binance platform. Investment duration varies, with 46.20% having traded for one to three years. These findings indicate that Sri Lankan cryptocurrency investors are predominantly well-educated males in the middle-income bracket, with a significant portion having moderate trading experience and a broad range of professional backgrounds.

Model Assessment

Examining the measurement models is the first step in evaluating PLS-SEM results. The next step is to assess the structural model to see if the measurement model meets all the required criteria. The final step is to interpret the PLS-SEM results with one or more robustness checks to support the stability of the results (Hair et al., 2017).

Assessing the Structural Model for Collinearity

Thorough PLS-SEM analysis depends on the research scope, model complexity, and presentation. It necessitates a robust evaluation of multi-collinearity among exogenous variables in the inner model. This entails identifying and addressing collinearity via variable removal, combination, or transformation into higher-order latent variables.

Table 2

Collinearity Statistics of VIF Inner Values

	INVD
FIN_LIT	1.293
HER	2.126
HEU	1.767
PRO	1.291
FIN_LIT x PRO	1.278
FIN_LIT x HEU	2.530
FIN_LIT x HER	2.645

According to Table 2, all variables in the model, including FIN_LIT, HER, HEU, PRO, and their interaction terms, exhibit VIF values below 3.5, indicating no collinearity issues with other independent variables (Hair et al., 2011). This confirms their suitability for inclusion in the structural model, where path coefficients will be evaluated next.

Assessment of Relevance of the Significance of the Structural Models Relationships

Path Significance and Hypothesis Testing of LOCs

Figure 3

Path Coefficient of LOCs

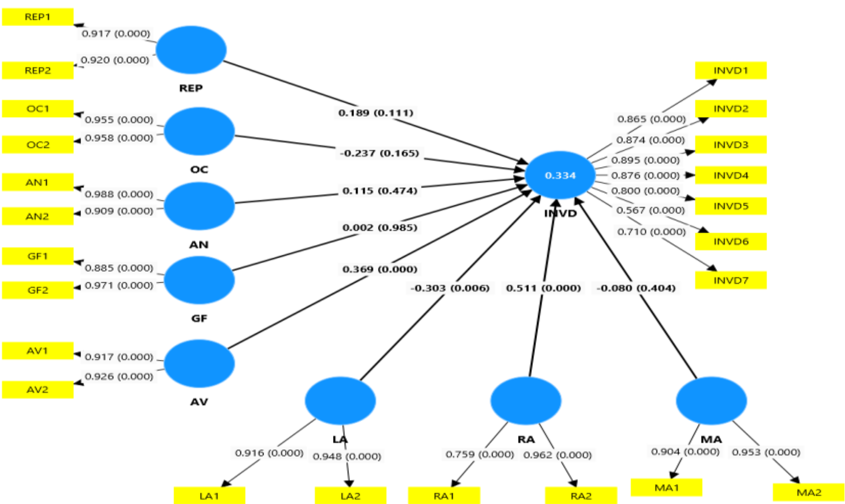


Table 3 indicates that the relationships REP->INVD, AN->INVD, GF->INVD, OC->INVD, and MA->INVD are non-significant, as their confidence intervals include zero, their *t*-statistics are below 1.96. Consequently, these hypotheses are rejected. On the other hand, the relationships AV -> INVD, LA -> INVD, and RA -> INVD are significant, as their confidence intervals do not include zero, and their *t*-statistics are above 1.96, leading to the acceptance of these hypotheses. Among the significant relationships, RA has the most substantial influence on INVD, followed by AV and LA.

Table 3

Significance of LOCs against INVD

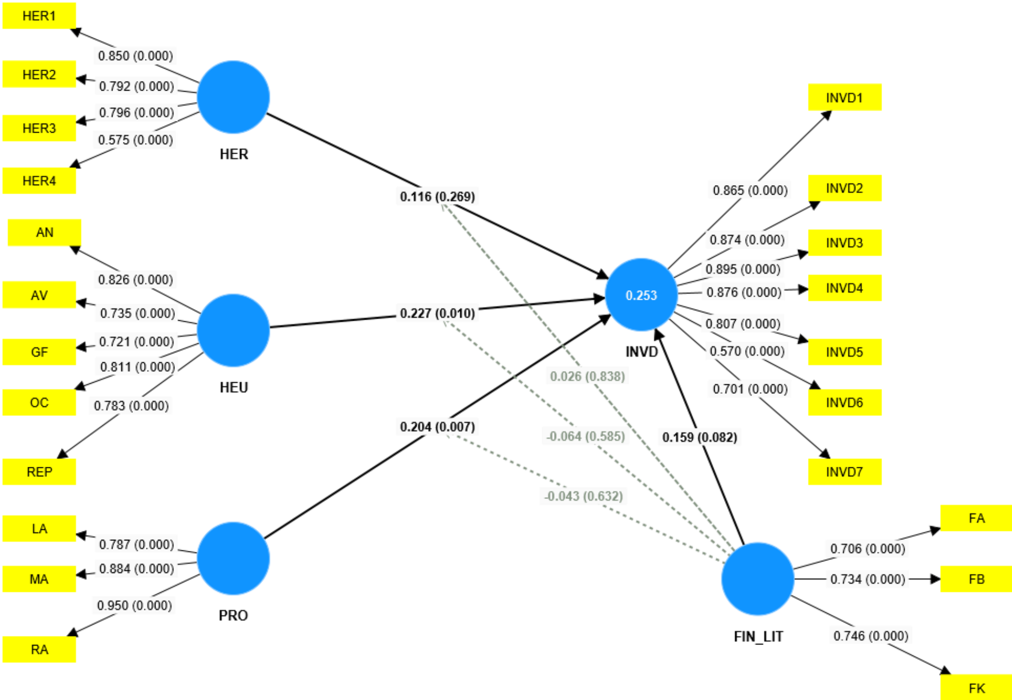
	Original sample (O)	**Sample mean (M)**	**Std Dev (STDEV)**	**Confident interval bias corrected**		***t* statistics (|O/ STDEV|)**	***p* values**	**Result**
				2.50%	**97.50%**			
REP -> INVD	0.189	0.175	0.118	-0.038	0.426	1.595	0.111	Rejected
AN -> INVD	0.115	0.115	0.161	-0.195	0.441	0.716	0.474	Rejected
AV -> INVD	0.369	0.376	0.08	0.199	0.515	4.610	0.000	Accepted
GF -> INVD	0.002	0.006	0.125	-0.247	0.247	0.019	0.985	Rejected
OC -> INVD	-0.237	-0.224	0.17	-0.589	0.082	1.389	0.165	Rejected
LA -> INVD	-0.303	-0.249	0.11	-0.534	-0.148	2.743	0.006	Accepted
RA -> INVD	0.511	0.466	0.144	0.256	0.802	3.545	0.000	Accepted
MA -> INVD	-0.08	-0.075	0.095	-0.284	0.092	0.834	0.404	Rejected
			Reference	No zero between		>1.96	<0.05	Rejected

Path Significance and Hypothesis Testing of Main Constructs (HOCs)

The PLS-SEM model findings, depicted in Figure 4, reveal the standardised regression coefficients for each path connection, with an R^2 value of 0.253 displayed within the endogenous latent variable's circle. Figure 4 identifies HEU (0.227) as the most influential factor for investment decisions, followed by PRO (0.204) and HER (0.116) as the least influential.

Figure 4

Path Coefficients of the Model



Initially, six main hypotheses were developed. The first three focused on the impact of behavioural biases on investment decisions, considering herding, heuristics, and prospect factors as independent variables. Al-Mansour (2020) suggests that assessing these biases individually offers a more accurate interpretation. Therefore, H_1, H_2, and H_3 were tested using PLS-SEM analysis. After ensuring the measurement model met all requirements, the SEM-PLS bootstrapping results were summarised in Table 4.

Table 4

Significance of HER, HEU and PRO against INVD

	Original sample (O)	Sample mean (M)	Std Dev (STDEV)	confident interval bias corrected 2.50%	97.50%	*t* statistics (|O/ STDEV|)	*p* values	Result
HER -> INVD	0.116	0.113	0.105	-0.078	0.334	1.105	0.269	Rejected
HEU -> INVD	0.227	0.239	0.088	0.038	0.380	2.593	0.010	Accepted
PRO -> INVD	0.204	0.213	0.076	0.040	0.331	2.678	0.007	Accepted
			Reference	No zero between		>1.96	<0.05	

According to Table 4 and the Smart PLS bootstrapping output, the HER->INVD relationship has a *t*-value below 1.96 (1.105), and a BC confidence interval that includes zero (-0.078, 0.334), indicating no significant impact. Conversely, the HEU->INVD relationship shows a *t*-value above 1.96 (2.593), and a BC confidence interval excluding zero (0.038, 0.380), confirming a significant impact. Similarly, the PRO->INVD relationship has a *t*-value above 1.96 (2.678), and a BC confidence interval excluding zero (0.040, 0.331), indicating a significant impact. Thus, hypothesis H_1 is rejected, while H_2 and H_3 are accepted. HEU (0.227) is the most influential factor, followed by PRO (0.204) and HER (0.116). A one-unit change in HEU increases INVD by 0.227, with similar effects for PRO, HER, and so on.

Hypothetical Relationships of Moderating Variable on the Behavioural Biases and Investment Decisions

In this study, hypotheses (H_4, H_5, and H_6) explore how financial literacy moderates relationships between behavioural biases (herding, heuristics, and prospect factors) and investment decisions. According to Table 5, the interaction terms involving HER, HEU, and PRO with INVD have *t* values of 0.204, 0.547, and 0.478, respectively. Additionally, their 95% bias-corrected bootstrap confidence intervals (-0.201, 0.294), (-0.328, 0.136), and (-0.241, 0.121) all include zero. These results indicate that financial literacy does not significantly moderate the relationships between these behavioral biases and investment decisions. Therefore, hypotheses H_4, H_5, and H_6 are rejected. As per the guidelines by Hair et al. (2017), the subsequent stage is to evaluate R^2 and interpret their impact, as shown in Figure 3.

Table 5

The Significance of Moderating Variable on Behavioural Biases and Investment Decisions

	Original sample (O)	Sample mean (M)	Std Dev (STDEV)	confident interval bias corrected 2.50%	97.50%	*t* statistics (|O/ STDEV|)	*p* values	Decision
FIN_LIT x HER -> INVD	0.026	0.007	0.126	-0.201	0.294	0.204	0.838	Rejected
FIN_LIT x HEU -> INVD	-0.064	-0.028	0.117	-0.328	0.136	0.547	0.585	Rejected
FIN_LIT x PRO -> INVD	-0.043	-0.039	0.09	-0.241	0.121	0.478	0.632	Rejected
			Reference	No zero between		>1.96	<0.05	

Assessment of the Level of R^2

The next step after ensuring collinearity is within acceptable limits (Hair et al., 2017) involves evaluating the R^2 values of the endogenous variables, as depicted in Table 6.

Table 6

R^2 Values

	R-square	R-square adjusted
INVD	0.253	0.218

The model's predictive capability is established with an R^2 value of 0.253, as shown in Table 6, indicating that 25.3% of the variations in investment decisions can be explained by factors like herding behaviour, heuristics, prospect factors, and financial literacy.

Assessment of the f^2 Effect Size

Table 7

f^2 Values

	INVD
FIN_LIT	0.026
HER	0.008
HEU	0.039
PRO	0.043
FIN_LIT x PRO	0.002
FIN_LIT x HEU	0.003
FIN_LIT x HER	0.000

The effect size f^2 measures the contribution of an exogenous construct to the R^2 value of an endogenous latent variable, with values in Table 7 indicating this contribution. According to Hair et al. (2017), f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively. Cohen (1988) similarly categorises f^2 values over 0.35 as large, over 0.15 as medium, and over 0.02 as small. As a result, FIN_LIT, HEU, and PRO have small effects on INVD.

Predictive Relevance of the Model (Q^2)

According to Hair et al. (2019), positive Q^2 values indicate significant predictive relevance of exogenous constructs to endogenous variables in a PLS path model. In this study, the Q^2 value of 0.138, shown in Table 8, suggests moderate predictive accuracy, affirming that factors such as herding behavior, heuristics, prospects, and financial literacy indeed influence investment decisions.

Table 8

Predictive Relevance of the Model (Q2)

	Q^2predict
INVD	0.138

Model Fit Summary of PLS-SEM

In PLS-SEM, the model fit summary assesses how well the model aligns with the observed data. Key indices like SRMR, d_ULS, and d_G indicate overall fit, with lower values showing better fit. The measurement model fit is evaluated using outer loadings, composite reliability (CR), and average variance extracted (AVE) to ensure reliability and validity. To determine relationship strength and predictive accuracy, the structural model fit takes into account path coefficients, R^2 values, f2 effect sizes, and predictive relevance (Q^2). Bootstrapping provides stability and significance for parameter estimates, ensuring model robustness and validity for credible research outcomes (Hair et al., 2017; Henseler et al., 2016). Following a conservative approach, according to Table 9, an SRMR value of less than 0.08 indicates a good fit (Hair et al., 2017).

Table 9

Model Fit Summary

	Saturated model	**Estimated model**	**Reference Value**
SRMR	0.062	0.073	<0.08
d_ULS	3.306	4.298	
d_G	1.588	1.665	
Chi-square	1376.222	1562.576	
NFI	0.875	0.83	>0.9

Discussion

The study investigates the impact of herding, heuristics, and prospect factors on cryptocurrency investment decisions in Sri Lanka, with financial literacy examined as a moderator. Traditional finance theory posits that investors evaluate all options before deciding, contrasting with behavioral finance, which suggests decisions are influenced by experience, judgment, and social trends (Lusardi & Mitchell, 2011). Behavioural biases such as herding, representativeness, anchoring, gambler's fallacy, overconfidence, availability bias, loss aversion, regret aversion, and mental accounting were analysed to understand their influence on decision-making. Demographically, the sample is predominantly male, aged 25–45, with bachelor's degree holders in the majority, earning between Rs.100,000 and Rs.150,000, and primarily employed in the private sector. Most participants traded cryptocurrencies through platforms like Binance with less than three years of trading experience.

Findings indicate that herding behaviour among Sri Lankan cryptocurrency investors is insignificant, possibly due to market size and regulatory uncertainties. This aligns with similar studies on behavioral biases in financial markets (Adiputra et al., 2023; Ranaweera & Kawshala, 2022; Setiawan et al., 2018). Representativeness, anchoring, gambler's fallacy, and overconfidence biases did not significantly influence investment decisions. The findings are consistent with the few studies conducted on behavioural finance and investment decisions by Mahadevi and Haryono (2021); Stockl et al. (2013); and Yuniningsih and Wikartika (2023).

Availability bias emerged as the most impactful heuristic factor among Sri Lankan crypto currency investors, facilitating quicker decisions based on readily available information, as the studies found, consistent with the findings of Le Luong and Ha (2011). A study conducted by Sachithra and Rajapaksha (2023) has found that heuristic-driven biases have a large effect on cryptocurrency adoption, bringing about a 48% negative variation in cryptocurrency adoption decisions of the Sri Lankan cryptocurrency investors. Prospect theory biases, particularly loss aversion, have a significant negative impact on the Sri Lankan cryptocurrency investors, and the result is consistent with Hwang (2024), and Khan et al. (2017). Regret aversion has a significant positive influence on investment decisions; the result is consistent with Putri and Hikmah (2020) and Ardini et al. (2023). The finding that mental accounting bias has no significant impact is consistent with the findings of Pratiwi and Puspawati (2022) and Mahadevi and Haryono (2021).

Financial literacy did not moderate the effects of behavioural biases on decision-making, suggesting that practical decision-making skills may outweigh theoretical knowledge in volatile markets like cryptocurrencies. This finding is like Hildebrandus et al. (2015), Sorongan (2022), and Wijaya et al. (2023). Overall, heuristic and prospect factors significantly influence cryptocurrency investment decisions in Sri Lanka, while herding behaviour and financial literacy play minor roles. These findings underscore the need for further research to develop tools aiding investors in mitigating cognitive biases' impacts on investment decisions.

Conclusion, Implications and Future Research

The research findings confirm that examined biases significantly affect investment decisions in the highly volatile cryptocurrency market, which is consistent with the behavioural theories discussed. The findings indicated that heuristic and prospect factors significantly affect the investment decisions of Sri Lankan cryptocurrency investors. However, the herding behaviour was found to be insignificant. Key findings show the lack of influence of herding behaviour, likely due to a small investor base and regulatory uncertainties; Additionally, this study investigated how financial literacy moderates the relationship between behavioral biases and investment decisions. While financial literacy is generally regarded as a crucial element for stabilising financial decision-making, this study did not find a significant moderating effect in the context of cryptocurrency investments in Sri Lanka.

The findings of the study have a practical and theoretical significance which are crucial for understanding and explaining investor behaviour in cryptocurrency markets in Sri Lanka. From a theoretical perspective, this study contributes to the existing literature where the findings of the study contribute to the growing literature on cryptocurrency investors, a field seldom explored in the Sri Lankan context. Further, this study provides greater insight into how behavioural biases influence the investment decisions of Sri Lankan cryptocurrency investors adding theoretical novelty through investigating the moderating effect of financial literacy.

From a practical perspective, the findings of the research are significant. The study proposes a framework for future research on behavioural finance in diverse emerging markets to better understand investor behavior. Sri Lankan context, educational programmes need to be developed focusing on enhancing financial literacy and helping investors make more rational decisions by minimising the impact of behavioural biases, assisting policymakers in creating regulations and frameworks that support informed investment practices and protect investors from impulsive decisions influenced by biases and enhanced decision-making.

The limitations of the study include a small, potentially unrepresentative sample, limiting its generalisability beyond Sri Lanka. Self-reporting bias and a cross-sectional design affect result accuracy, as they may not fully capture evolving biases in the volatile cryptocurrency market. The focus on general financial literacy may not reflect practical skills, and omitted factors like prior investment experience and socio-economic status could influence behaviours. High market volatility and regulatory uncertainty further complicate the distinguishing between behavioural biases and market dynamics. Further research should validate these findings with a larger, more diverse sample. Exploring institutional cryptocurrency investor behavior, comparing across nations, and studying the role of technical analysis knowledge in moderating behavioural influences on investment decisions are also crucial. Investigating investor behaviour across different market trends, like bull and bear markets, would yield valuable insights.

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