Original Research Article

Antecedents of the Adoption of Cryptocurrency Investment: The role of behavioural bias in an emerging market

Abstract

Cryptocurrencies have become a popular discussion in the global economy as an increasing number of people adoptthese despites their recent conception. As a result, governments worldwide are racing to incorporate assets into their legal frameworks. While Sri Lanka does not have a legal framework for such assets, there is a growing base for cryptocurrencyinvestors in the country. This study analyzes the antecedentsthat drive Sri Lankan investors towards cryptocurrency investments and the influence of commonly known behavioral biases among these investors to examine the validity of behavioral finance theories in cryptocurrency markets. A structured questionnaire was distributed on social media platforms, which yielded 158 responses. Descriptive analysis was used to evaluate the demographic characteristics of the respondents, and PLS-SEM was used to examine the path model analysis of associations among the study variables. The findings suggest that the majority of respondents are males under 35 years of age with high educational qualifications, and that technical, economic, social, and personal factors are their main adoption motivators. The analysis of behavioral biases suggests that heuristic-driven and frame-dependent biases influence cryptocurrency adoption decisions. As a highly discussed topic in today's world, there is a lack of studies focusing on the adoption motivators and behavioral biases of cryptocurrency investors. These findings provide valuable insights and enrich the existing knowledge in the domain of cryptocurrency, as this study is a pioneering endeavor focusing on behavioral biasesin cryptocurrency markets.

Keywords: Cryptocurrency; Behavioral biases; Prospect theory;Sri Lanka; Adoption

Introduction

Over the last decade, the emergence of new technologies has resulted in major changes in business activities (Liébana-Cabanillas *et al*., 2014). The popularity of the Internet and the development of new mobile and electronic payment methods has fundamentally changed the way of doing business, making payments, and even simple day-to-day tasks such as grocery shopping (Guych*et al*., 2018). Among these innovations, blockchain technology and digital currencies have taken the world by storm by becoming tactical assets and investment tools for many organizations within just a few years from the initial conception. Bitcoin, known to be the world's first cryptocurrency, was introduced by a pseudonymous entity named Satoshi

Nakamotousing a white paper in 2008 (Lammer *et al*., 2019). Bitcoin quickly rose to fame and in the meantime, also helped spur the creation of many other new cryptocurrencies commonly termed as 'altcoins' (stands for alternative cryptocurrencies) as Bitcoin is open source and the source code is freely available to other developers who altered it to create different other similar cryptocurrencies. Together with the expected value of cryptocurrencies as an investment tool, they have spurred the creation of altcoins, leading to an exponential growth in the total size of the cryptocurrency market *(Bouri et al*., 2018). As per CoinGecko, the total number of cryptocurrencies in circulation surpassed 12,000 in September 2022, with total market capitalization exceeding USD 1 trillion (CoinGecko, 2022).

As a relatively novel concept, there is a lack of studies on the cryptocurrency market and traders. While such studies have been conducted in developed markets, where cryptocurrency adoption is more widespread and accepted,there is little to no previous literature on cryptocurrency traders in Sri Lanka. Moreover, the absence of a regulatory framework for cryptocurrency has also influenced investors' confidence and sentiment in Sri Lanka. Interestingly, Sri Lankan investors live in a collective culture, are influenced by their family and friends' suggestions and recommendations, and display herd behavior. They do not understand how their psychology, sentiments, and behaviors can affect their investment performance and returns. Therefore, understanding the demographic specifics of cryptocurrency investors in the country and the motivators that have driven them to adopt such novel tools remain unexplored.

Behavior is the aspect of individuals that changes according to their acquired information and knowledge, and investors invest based on available information and financial knowledge (Son and Park, 2019). Behavioral finance proposes that investors exhibit psychological and emotional behavior that sometimes diverges from rational behavior (Yoong and Ferreira, 2013). Sufficient literature and studies can be found on the behavioral biases of investors in various countries and how such biases have impacted stock market returns and individual portfolio returns. Pompian (2012) described behavioral biases as the tendency to make decisions that result in foolish investment decisions because of their mental decline. There are several biases in human psychology (Hoffmann *et al*., 2010). However, a literate investor can neglect their biases and make sound financial decisions regarding cryptocurrency investments (Son and Park, 2019). In the Sri Lankan context, no published studies have determined the validity of these behavioral biases among cryptocurrency traders in the country. As the existing literature is puzzling, this study examines whether several behavioral biases can affect cryptocurrency investors' investment decisions in Sri Lanka. Accordingly, this study aimed to:

- Identify the different demographic characteristics of the Sri Lankan cryptocurrency investors;
- Examine what adoptive motivators drive Sri Lankan investors towards cryptocurrency investments;and

- Examine the influence of behavioral biases on cryptocurrencytraders' investment decisions in Sri Lanka.

Literature Review

Cryptocurrency and characteristics of cryptocurrency investors

Nian and Chuen(2015)define cryptocurrencies as a type of electronic cash that facilitates direct peer-to-peer transactions without the intermediary function being played by a mediating financial institution, as in a traditional bank-based transaction. The definition of the European Central Bank (2015) indicates that cryptocurrencies are tools that have digital value, are not issued by a monetary authority, and in some situations, are used as an alternative to traditional money.

Cryptocurrencies have only existed for a little more than a decade, given that the first cryptocurrency, Bitcoin, was introduced in 2008 (Vranken, 2017). However, during this short period, Bitcoin has received unmatched popularity and has also facilitated the creation of all other cryptocurrencies in existence today (Urquhart, 2016). Since the value of a digital coin that is not backed by any real-life physical assets was questioned, early adoption was slow; however, cryptocurrencies became widely discussed and adopted a few years later (Böhme *et al.*, 2015). These cryptocurrencies were initially only used as an investment tool, albeit at present, the perception of the general public has been gradually changing as more corporations have begun accepting cryptocurrencies as a medium of exchange (Baur & Dimpfl, 2021). Major global corporations such as Microsoft, Tesla, PayPal, AT&T, Burger King, and Starbucks have taken initiatives to accept cryptocurrency payments in exchange for goods and services, essentially replacing fiat money (Baur & Dimpfl, 2021). Therefore, cryptocurrencies currently perform all the major functions of traditional money, namely, store of wealth, unit of account, and medium of exchange.

It should also be noted that, in the majority of countries, no legal framework has been developed to incorporate these digital assets into the rules and regulations of financial systems. In Sri Lanka, payments to acquire any digital assets using debits or credit cards are prohibited under the law, although cryptocurrencieshave not been included in the law (Economy Next, 2021).

While multiple studies have been conducted on the technical aspects of cryptocurrencies in different countries, studies focusing on cryptocurrency traders and their demographic characteristics are rather scarce, especially in South Asia. Using a publicly available dataset of cryptocurrency users worldwide, Bohr and Bashir (2014) discovered that the average age of the respondents was 33 years, with approximately 80% of the cryptocurrency users below 40 years of age. Moreover, Schuh and Shy (2015), in their research on U.S.-based Bitcoin owners, found that an average person who owns Bitcoin has a higher likelihood of being a younger, non-white male with comparatively low education level.

In a web-based survey of Australian and Chinese cryptocurrency investors, Xi *et al*. (2020) found that Chinese investors who belong to the 18 – 30 age group were relatively more willing to invest in cryptocurrencies, whereas in both Chinese and Australian surveys, females were found to be less willing to invest in cryptocurrencies than men. Shehhi *et al*. (2014), in a web-based survey of Asian cryptocurrency investors, found that 70% of the participants were below 35 years of age, 40% of the participants had professional grade jobs, and 37% were self-employed. Interestingly, the study found that 95% of cryptocurrency investors in the sample were male, with only 5% female cryptocurrency investors.

While the availability of studies on the demographic characteristics of cryptocurrency investors is limited, it can be observed that most prior literature highlights that relatively younger, male investors have a higher propensity to use and invest in cryptocurrencies.

Cryptocurrency adoption motivators

In addition to the demographic factors of cryptocurrency investors, it is also important to identify the factors that influence their adoption of cryptocurrencies. There have been attempts to use existing technology acceptance theories to examine users' intentions to adopt cryptocurrencies. Prior studies have used theories such as the diffusion of innovation, technology acceptance model, and unified theory of acceptance and use of technology (Alzahrani and Daim, 2019a).

Presthus and O'Malley and Nicholas (2017) investigated the motivators and barriers for the use of Bitcoin in the United States using a web-based survey and found technological curiosity to be the main factor motivating respondents to adopt Bitcoin, whereas Khairuddin*et al*. (2016) conducted an exploratory study on Bitcoin investors in Malaysia focusing on how users experience Bitcoin. The findings indicate the expected role of cryptocurrency in a revolution based on monetary assets, increased user empowerment, and the expectation that Bitcoin's real value is the main adoption motivator.

Other studies have found that the main factors influencing people's use of cryptocurrenciesarea high level of privacy, their use as an alternative payment system, and the anonymity of blockchain technology that facilitates illegal activities (Alzahrani and Daim, 2019b; Karlstrøm, 2014; Maurer *et al*., 2013). In addition, Bohr and Bashir (2014) used publicly available cryptocurrency traders' data and found that anonymity provided by cryptocurrencies, freedom to transact, and a lack of trust in the banking system were among the reasons for adopting cryptocurrencies. In summary, factors such as usefulness, ease of use, stability, security, anonymity, freedom, lack of trust in the banking system, acceptance as payment method, accessibility, and laws and regulations would motivate and foster the adoption of cryptocurrency.

Alzahrani and Daim (2019b) claimed that prior studies, mainly concerned with techno-centric aspects and addressing the multidimensional assessment of the adoption decision, are still limited. The authors then identified various technical, economic, social, and personal factors that influence the adoption decision, and developed a framework incorporating many such adoption motivators into four main perspectives: technical, economic, social, and personal, each including measurement criteria (Figure 1).

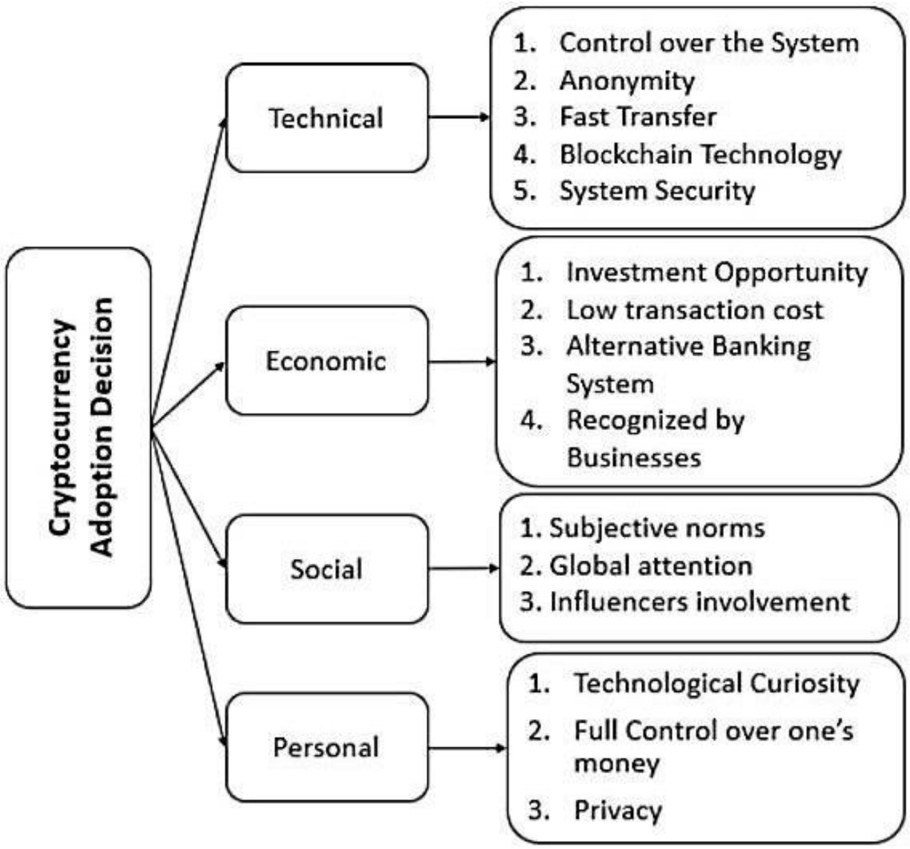

Figure 1: Cryptocurrency adoption motivators
Source: (Alzahrani and Daim, 2019b, p.4)

Technical factors include technology-related reasons such as fast transfer capability and system security as motivations to adopt cryptocurrencies. Prior studies have also revealed that cryptocurrencies have a very high level of anonymity (Bohr & Bashir, 2014). This is pseudo-anonymity, where the identities of the users are hidden with a private key. Fast transfer represents the time it takes to send or receive funds or transfer coins from one wallet to another, which seems to be nearly instantaneous. Blockchain technology reduces transaction costs and eliminates interference from middle parties. Cryptocurrency has a very high level of system security, and it is very difficult to take it down (Karlstrøm, 2014). Based on the above arguments, the following hypothesis is proposed:

H1: Technical factors affect the cryptocurrency adoption of Sri Lankan cryptocurrency investors

Economic factors include investment opportunities, transaction costs, banking system aspects, and acceptance as a payment method. The cryptocurrency market includes hthousands of altcoins, and may serve as an investment opportunity (Sas and Khairuddin, 2017).

Cryptocurrency transaction fees are very low compared to those of traditional banks. As such, the international remittance market specifically motivates cryptocurrency investments. In the technology space, cryptocurrencies have reached significant market capitalization. In this vein, cryptocurrencycan be used as an alternative banking system as it is not tied to a central authority. Presthus and O’Malley (2017) opined that cryptocurrency provides a viable solution for populations living in underdeveloped countries and provides solutions to potential economic problems, such as hyperinflation, inflation, fraud, and counterfeiting. Unstable monetary systems and highly volatile currencies in some countries appear to continuously change their prices. Thus, people living in countries with fluctuating and unstable exchange rates may be more interested in cryptocurrency and use it as a payment method (Maurer *et al*., 2013). The above arguments led us to hypothesize the following.

H2: Economic factors affect the cryptocurrency adoption of Sri Lankan cryptocurrency investors

The model developed by Alzahrani and Daim (2019b) focuses on the societal aspects of adopting new technologies, such as peer pressure and the involvement of influential figures for social reasons. The subjective norms construct is intended to capture social influence, which is defined as the degree to which an individual perceives that important others believe he or she should adopt and use cryptocurrency. Furthermore, global attention towards cryptocurrencies has increased and feeds into demand for cryptocurrencies. Although this is not universally recognized as an official payment currency, it is seen that people from different countries are observing economic reactions toward cryptocurrency prices (Khairuddin*et al*. 2016). Moreover, the positive comments and views of top business managers/owners influence people’s involvement in cryptocurrency (Chuen*et al*., 2017). Based on these points, the study postulated the following:

H3: Social factors affect the cryptocurrency adoption of Sri Lankan cryptocurrency investors.

Personal aspects appeal to curiosity and privacy as personal factors that affectcryptocurrency adoption decisions. There are innovators and early adopters of any technology driven by their curiosity toward new innovative solutions. Thus, curiosity toward new technology plays a role in the adoption of cryptocurrency (Krombholz*et al*., 2016). On the other hand, cryptocurrency systems give users full control over their own money. This creates an attractive feature to use cryptocurrency because users can send or receive whatever amount of money anywhere and whomever they wish to without any interference. Privacy is another vital factor when anyone thinks about wealth. In a cryptocurrency, no one knows how much one has received or spends. The existing banking system limits personal financial liberty, and perceives it as threatening users’ privacy. In this vein, the privacy of financial information is a major antecedent for cryptocurrency adoption. This study thus sets the following hypothesis:

H4: Personal factors affect the cryptocurrency adoption of Sri Lankan cryptocurrency investors.

In summary, the literature suggests that the cryptocurrency adoption level is increasing, and there are many factors influencing this adoption. Despite the many motivations for cryptocurrency adoption, a multi-criteria decision model needs to be developed to assess adoption factors. The multicriteria model can be combined with techno-centric, economic-centric, and consumer-centric aspects. Acknowledging the model developed by Alzahrani and Daim (2019b), this study utilized technical, economic, social, and personal factors to determine the main cryptocurrency adoption motivators of Sri Lankan investors, which, together with their demographic factors, could help policymakers formulate better targeted policies and laws.

Behavioral biases

Classical economics and finance models contain multiple theories that explain how individuals perceive risk and act logically and rationally to maximize their utility and satisfaction. However, in reality, people, especially investors, do not behave logically or rationally when making decisions. Therefore, classical theories can only explain, to a certain extent, how markets work. Behavioral finance attempts to make sense of the remaining unexplained part by combining the psychological and cognitive sciences to explain why individuals may sometimes act irrationally and illogically sometimes (Chira *et al*., 2011).

Behavioral finance is a highly researched area, with numerous studies pointing to the existence of various behavioral biases among investors and decision-makers in many countries across the world and their impact on market performance. Bouri *et al*. (2018) examined the presence of herding behavior, the tendency of investors to take similar trading decisions irrespective of the available information, within the cryptocurrency markets and found that cryptocurrency investors frequently display such behavior in stress situations.

The debate around the existence of biases in decision-making is rooted primarily in Kahneman and Tversky's (1979) prospect theory. The prospect theory aims to describe the actual behavior of people. They found that losses hurt about twice as much as gains make people feel good. In general, this explains how investors make decisions under certain risks. According to them, individuals assess their loss and gain perspective asymmetrically. Following prospect theory, scholars have categorized these biases in many different ways. Shefrin (2000) classified biases into two categories: heuristic-driven and frame-dependent biases. Pompian (2006, 2012) categorized these biases as cognitive and emotional. Montier (2002) indicated three broad categories: self- deception, heuristic simplification, and social interaction.

In the present study, we selected a set of biases to represent the categories proposed by Shefrin (2000): heuristic-driven and frame-dependent biases. The term heuristic is defined as the decisions made amid complexities, and conditions of uncertainty are mostly based on beliefs about the likelihood of uncertain events (Tversky and Kahneman, 1974); investors have a bias in their belief that will affect how they think and make decisions (De Bondt*et al*., 2008) as well as the use of experience and practical efforts, which is an effort to interpret information quickly by relying on experiences accompanied by intuition (Fromlet, 2001). Here, people tend to use rules of thumb to simplify decision-making processes and make faster decisions. However, investors frequently make mistakes in decision-making by using the rules of thumb as a basis in processing information. As Tversky and Kahneman (1974) classified, heuristic bias includes three types: representativeness, loss aversion, and anchoring bias. These three types were used to operationalize heuristic bias in this study.

Anchoring bias occurs when people rely excessively on the first information they find when making decisions. Investors exaggerated by this bias are inclined to underline their investment decisions primarily on one piece ofinformation that is first acquired.Frensidy (2016) opined that many investors in the capital market experience anchoring bias and that most continue to remember the buying price of shares in their portfolio. Representativeness bias occurs when people make decisions based on certain stereotypes, prior knowledge, or experience they have (Baker and Nofsinger, 2002).Thus, investors acquire information from the surrounding environment and ignore other sources. Interestingly, investors often believe that past return rates represent expected future returns (Ritter, 2003).Loss aversion refers to the tendency to avoid losses to acquire equivalent gains. Loss aversion is a tendency in which investors are so fearful of losses that they focus on trying to avoid a loss more than on making gains (Pompian, 2006). Investors tend to feel more stressed by potential losses than by potential gains with an equivalent value. Therefore, they are more prudent to invest in reducing the risk of losses (Barberis&Thaler, 2003).Recently, Gurdgiev and O'Loughlin (2020) discovered evidence of anchoring behavior in cryptocurrency markets. Thus, based on arguments in the literature, we propose the following hypothesis:

H5: Heuristic-driven biases affect cryptocurrency adoption by Sri Lankan cryptocurrency investors.

The decision-making process is highly dependent on how information is framed or presented (Frensidy, 2016). Framing is a direct application of prospect theory, which is heavily influenced by how problems or data are presented (Tversky and Kahneman, 1986). As the theory insists, individuals are usually more sensitive to negative frames than to positive ones. Moreover, Thaler (1985) claimed that individuals' decisions are framed inside different accounts and that they do not consider interactions among multiple decisions. Frensidy (2016) further argued that first impressions usually receive more weight than the information that comes after; therefore, the information placed behind them receives less attention. It is further noted that one's concentration level may decrease with an increase in the amount of information to be absorbed. These factors lead to frame-dependent biases.Craggs (2016) demonstrated the presence of framing bias among Bitcoin users worldwide. This study thus sets the following hypothesis:

H6: Frame-dependent biases affect cryptocurrency adoption by Sri Lankan cryptocurrency investors.

Methodology

From the previous discussion in the literature, it can be seen that technology, economic, social, and personal factors,heuristic-driven biases, and frame-dependent biases are empirically connected and influence investors' cryptocurrency adoption decisions. Keeping this in mind, the study proposes the following conceptual model (Figure 2):

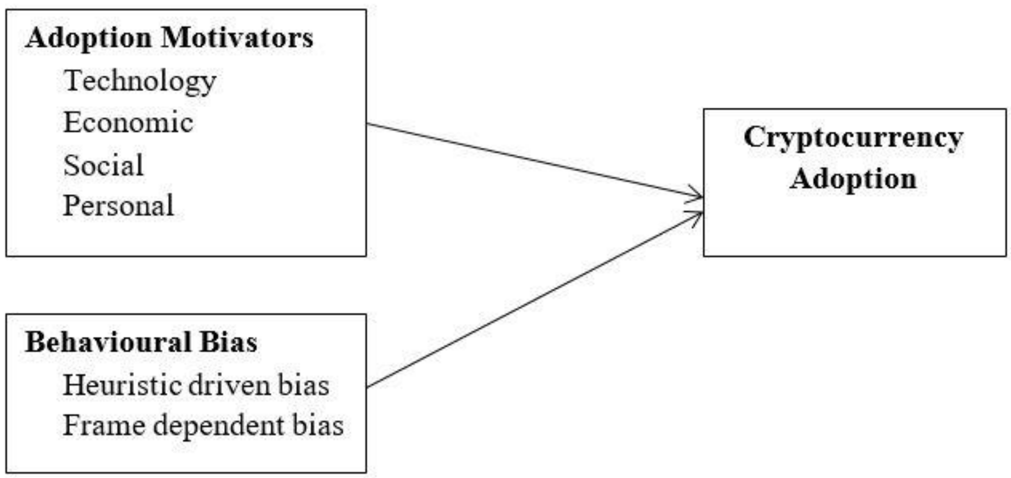

Figure 2: Conceptual model

Research design and survey procedure

A cross-sectional research design was considered in this study, which aims at collective quantifiable primary data to examine the effects of situational factors and behavior biases on the investment decisions of cryptocurrency traders in Sri Lanka. The respondents are individuals who currently own, use, and/or invest in cryptocurrencies. Therefore, the target population included all cryptocurrency investors in Sri Lanka. However, there is no centralized registry of such individuals, given that cryptocurrencies are not transacted using a centralized exchange with regulatory boundaries. According to available data from newspaper resources for the current Sri Lankan member base of the most widely used cryptocurrency trading application, Binance, it can be loosely estimated that the population would entail close to 4000 investors (Handagama, 2021). As there is no officially recognized sample framework, this study has to utilize a non-probability sampling design. The sample of this study is restricted to a specific group of investors who can provide the required information; therefore, this study employs a purposive sampling method. To determine the representativeness of the sample, following Krejcie and Morgan's (1970) sample size calculation, around 350 investors were targeted for participation. Out of those, the questionnaire yielded 158 responses.The respondents' profiles were segregated based on demographics (Table I).

Table I: Demographic characteristics of respondents

Variables	Measuring Group	Frequency	Percentage (%)
Gender	Male	122	77
	Female	36	23
Age (years)	18-25	80	51
	26-35	68	43
	36-45	10	6
	46-60	0	0
	Above 60	0	0
Marital status	Married	59	37
	Unmarried	99	63
Highest educational qualification	Ordinary Level (O/L)	7	4
	Advanced Level (A/L)	13	8
	Bachelor's degree	78	49
	Master's degree	33	21
	Doctorate	0	0
	Other professional qualification	27	17
Employment status	Employed	118	75
	Un-employed	40	25
Current position	Entry level	29	25
	Executive level	45	38
	Managerial level	22	19
	Top-management	7	6
	Other	15	13
Experience (years)	Less than 1	50	32
	1 -5	82	52
	6-10	22	14
	Above 10	4	3
Monthly income (Rs.)	Less than 50,000	30	19
	50,000 - 100,000	62	39
	100,000 - 200,000	41	26
	200,000 - 500,000	20	13

	Above 500,000	5	3
Monthly savings percentage out of monthly income	No savings	18	11
	Less than 10%	32	20
	10% - 20%	34	22
	20% – 50%	50	32
	Above 50%	24	15
Residential status	Own home	19	12
	Rental	32	20
	Living with parents	93	59
	Other	14	9

The survey primarily tested ten different demographic characteristics of Sri Lankan cryptocurrency investors (Objective 1). As shown in Table I, 77% of the respondents were male, and only 23% were female, conforming to the findings of previous studies on cryptocurrency investors in different countries. Investing and technology are often considered male-dominated fields, while women also invest in stock markets and other opportunities, and the field is mostly concentrated on male investors. The survey also shows that 51% of cryptocurrency investors are within the age group of 18-25 and 43% are between 26-35. Interestingly, no respondents were in the age group above 45, also conforming to empirical studies that mostly younger age cohorts tend to adopt new technologies faster.

As per the findings, 37% of the respondents were married and 63% were unmarried/separated/divorced. Marital status plays a major role in an individual's commitment to investment management, and the majority of unmarried cryptocurrency investors may be due to the high percentage of younger respondents. The survey also revealed that Sri Lankan cryptocurrency investors had high educational qualifications, with 49% of the respondents carrying a bachelor's degree, 21% carrying a master's degree, and 17% with other professional qualifications. Only 4% of the respondents had their highest educational qualification at an ordinary level and 8% at an advanced level.

The results on the employment status of the respondents show that 75% were employed and only 25% were unemployed. Out of the currently employed population, 25% were at the entry level, 38% were at the executive level, 19% were at the management level, and 6% were at the top management level. This is also in line with the age structure of the respondents, where the majority are within the younger age groups and therefore could still be in the entry- and executive-level jobs. Regarding the monthly income of the respondents, the results reveal that 19% earn less than Rs. 50,000 monthly, 39% earn between Rs. 50,000 – 100,000, 26% earn between Rs. 100,000-200,000 and 13% earn between Rs. 200,000-500,000. The smallest percentage (3%) earned more than Rs.500,000. Of this monthly income, 11% of the respondents had no savings, while 20%, 22%, and 32% saved less than 10%, 10%–20%, and 20%–50%, respectively. Fifteen percent of the respondents indicated that they had saved more than 50% of their monthly income. Regarding the residential status of the respondents, only 12% had their own homes, while 20% lived in rented spaces. The majority of the respondents (59%) indicated that they lived with their parents.

Operationalization of the variables

Table II presents how each independent variable used for the hypothesis development, namely technical, economic, social, personal, heuristic-driven, and frame-dependent biases,and the dependent variable cryptocurrencyadoption are measured to achieve the study objectives. The adoption level of cryptocurrency is measured by the number of logins, trades, and average transaction value. Technical and economic factors had four measurement items each, while social and personal factors had three measurement items each. For heuristic-driven and frame-dependent biases, three and four measurement items were used, respectively. These measurement items were presented as five-point Likert scale statements to the respondents to obtain the data. To measure adoption motivators, a five-point Likert scale was used: 1 = strongly disagree and 5 = strongly agree with a neutral option in the middle. For the measurement items of cryptocurrency adoption,the number of logins per week was used with a five-point scale: 1 = 1 time or less, 2 = 2 to 5 times, 3 = 6 to 15 times, 4 = 16 to 50 times, and 5 = more than 50 times.

Table II: Operationalization of variables

Variable	**Measurement Item**	**Source**
Cryptocurrency adoption (Adoption)	Number of login times to the crypto account per week (A1) Number of cryptocurrency trades/transactions per week (A2) Average transaction value (A3)	(Al-Amri et al., 2019)
Technical factors (Tech)	Control over the system (T1) Anonymity (T2) Fast Transfer capability (T3) Blockchain technology (T4) System security (T5)	(Alzahrani & Daim, 2019a,b)
Economic factors (Econ)	Investment opportunity (E1) Low transaction cost (E2) Alternative banking system (E3) Recognition by businesses (E4)	
Social factors (Social)	Subjective norms (S1) Global attention (S2) Influencers' involvement (S3)	
Personal factors (Personal)	Technological curiosity (P1) Full control over one's money (P2) Privacy (P3)	

Behavioural Bias Heuristic driven bias	Rely on the high rate of return achieved in the market I hold onto my loss-making coins for as long as it takes to recover the shortfalls on them. I am always confident I will make gain when trading in the market	(Ackert and Deaves, 2010) (Frensidy, 2016)
Frame dependent bias	I sometimes change my mind on investment just because someone talks to me about it in a different way Other people manner of representing a previously decided issue contributes to a change of mind on an investment The recent collapse of the market is enough reason for me never to invest in the cryptocurrency market again The recent short-term fluctuations in the value of my investments are of more concern to me than the long-term implications.	(Frensidy, 2016)

Data collection

The study uses primary data for the purpose of achieving its objectives collected using the survey method through a structured questionnaire, where questions are designed to be close-ended and structured using ranking and Likert-scale question forms. The questionnaire included 45 questions in 3 segments for demographic factors, adoption motivators, and behavioral biases. To collect data on the respondents' demographic profiles, 10 questions were prepared covering age, educational and professional background, and saving habits. The adoption motivators and behavioral bias segments both include questions on a five-point Likert scale with statements describing each sub-category. The questionnaire is web-based, created using the Google form application, and was distributed among the targeted sample through different online means, such as social media groups primarily focused on Sri Lankan cryptocurrency investors. The questionnaire was distributed to such groups on several social media platforms, including Facebook, WhatsApp, and Telegram. Data were collected for a period of six months, from September 2021 to March 2022.

Data analysis

In the current research, to examine the planned hypotheses, the partial least squares structural equation modeling (PLS-SEM) technique was used. First, we tested the measurement model (reliability and validity), and then computed the structural model (bootstrapping). For the measurement model, factor loadings were used to assess inter-item reliability, while viewing a cut-off value of 0.70 (Munir, 2018). The average variance extracted (AVE) describes convergent validity. AVE is used to establish the amount of change and variance that a latent variable can expound. According to Ramayah*et al*. (2017), AVE values equal to 0.5 or higher leads to convergent validity. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR), and these values should be above the threshold value of 0.70 (Hair *et al*., 2014). Table III lists the measurement model computations used in this study.

Table III: Measurement model computation

Variable	No. of Items	KMO Value	Bartlett's Test of Sphericity Chi-Square	Total Variance Explained	AVE	Cronbach's Alpha	CR
Cryptocurrency adoption	3	0.707	842.399	78.11	.75	.769	.754
Technical Factors	5				.73	.830	.832
Economic Factors	4				.58	.735	.886
Social Factors	3				.73	.886	.829
Personal factors	3				.73	.822	.798
Heuristic driven bias	3				.662	.731	.764
Frame dependent bias	4				.631	.766	.864

To ensure discriminant validity, the AVE of each latent variable should be higher than the squared correlations with all other latent variables. Table IVillustrates that the construct shares more variance with its indicators than any other construct.

Table IV: Discriminant validity

	Adoption	**Tech**	**Econ**	**Social**	**Personal**	**Heuristic**	**Frame**
Adoption	**0.75***						
Tech	0.352	**0.73***					
Econ	0.091	0.037	**0.58***				
Social	0.422	0.275	0.154	**0.73***			
Personal	0.330	0.281	0.045	0.412	**0.73***		
Heuristic	0.412	0.147	0.031	0.271	0.114	**.66***	
Frame dependent	0.454	0.251	0.107	0.411	0.248	0.371	**.63***

Next, the model fitness was examined to determine the goodness of the proposed model. The measures of model fit include standardized root mean square residual (SRMR) and normed fit index (NFI), which are based on the value of chi-square ($\chi 2$),which must be significant at the 5% level of significance. Ramayah*et al*. (2017) stated that the value of SRMR should be less than 0.08 as acceptance criteria, and a perfect model fit can be attained if the SRMR value is zero. The value of NFI must be higher than 0.90, to meet the acceptance criteria, and good model fitness can be achieved when NFI is close to 1. The study results showed an SRMR value of

0.066 and NFI value of 0.894. The values of SRMR and NFI also depend on the acceptance criteria. Our model is statistically fit and sound, and meets the quality criteria of a good model.

After fulfilling the requirements of the measurement model, the structural model was tested to determine the significance of the hypothesis. The assessment of the model's quality is based on its ability to predict endogenous constructs. The following criteria facilitated this assessment: coefficient of determination (R^2), path coefficients, and effect size (f^2). The R^2 is a measure of the predictive accuracy of the model. The result revealed that $R^2 = 0.86$, indicating 86% of the exogenous variable's combined effect on the endogenous variable. Path coefficients represent the hypothesized relationships that link the constructs. Finally, the effect size was evaluated to determine the significance of each factor in influencing investment decisions. F-square is computed to illustrate the effect size of each variable on cryptocurrency adoption.Based on the f^2 value, the effect size of the omitted construct for a particular endogenous construct can be determined such that 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Table V). In the present study, technical, economic, social, personal, heuristic-driven, and frame-dependent biases significantly contributed 86% toward the decisions taken by investors to trade cryptocurrency (Table V).

Table V: Path analysis results

Hypothesis	**Path coefficient**	**Sig.**	**F-square**
H1: Technology factors to cryptocurrency adoption	0.400	0.000	0.510
H2: Economic factors to cryptocurrency adoption	0.431	0.000	0.459
H3: Social factors to cryptocurrency adoption	0.361	0.000	0.440
H4: Personal factors to cryptocurrency adoption	-0.202	0.000	0.133
H5: Heuristic driven bias to cryptocurrency adoption	-0.479	0.000	0.552
H6: Frame dependent bias to cryptocurrency adoption	0.538	0.000	0.511

As shown in Table V, the effect sizes of technical, economic, social, heuristic-driven, and frame-dependent biases on cryptocurrency adoption decisions are large, with valuesgreater than 0.35. Among these factors, heuristic-driven biases bring about 48% negative variation in cryptocurrency adoption decisions. However, the effect size of personal factors on cryptocurrency adoption decisions was lower than 0.15.

Discussion

The findings of this study regarding the demographic characteristics of cryptocurrency investors in Sri Lanka appear to be consistent with the past findings of similar studies focusing on cryptocurrency investors. This study revealed that the majority (77%) of Sri Lankan cryptocurrency investors were male and young, as all respondents were below 45 years of age, while 94% of respondents were below 35 years of age.In a study of cryptocurrency users worldwide, Bohr and Bashir (2014) found that the average age of users was 33 years, with approximately 80% of cryptocurrency users being below 40 years of age. Xi *et al*. (2020) found that Chinese investors in the age group of 18-30 were more willing to adopt cryptocurrencies, whereas Shehhi*et al*. 's(2014) study revealed that 70% of Asian cryptocurrency investors were below 35 years of age, while 40% were professionally employed. Moreover, Shehhi *et al*. (2014) found that 95% of cryptocurrency investors were male. This study also discovered that Sri Lankan cryptocurrency investors have a high level of educational qualifications, with 49% of respondents having bachelor's degrees and 21% having master's degrees as their highest level of education. The majority (75%) of the respondents were employed, with 84% with less than five years of work experience and 58% with monthly income less than Rs. 100,000. The finding of higher levels of education seems to contradict the findings of Bohr and Bashir (2014), who indicated that the average cryptocurrency investor in the US is more likely to be a male with low levels of education.

These findings further show that technological factors have a significant effect on cryptocurrency adoption in Sri Lanka. Control over the system, anonymity, fast transfer capability, blockchain technology, and system security were the technological sub-factors tested in this study. This finding is consistent with some previous studies where researchers have found factors related to technology to be an adoption motivator for cryptocurrencies, which contradicts previous findings. Presthus and O'Malley (2017) found technological curiosity to be the main adoption motivator, while Bohr and Bashir (2014) found anonymity to be the main reason why people adopt cryptocurrencies. However, Alzahrani and Daim (2019a),who conducted a study with the same adoption motivators as this study, did not find technical factors to be significant adoption motivators for cryptocurrency investors. On the other hand, the findings of this study are in line with the demographic characteristics of the respondents, as the respondents of the survey were found to be from younger age groups who are more interested in technical aspects.

With regards to the economic factors, the study's findings show that economic factors have a significant large effect oncryptocurrency adoption in Sri Lanka. The sub-factors included in the economic factors for the study were investment opportunity, low transaction cost, alternative banking systems, and recognition by businesses. This is in line with and similar to past research findings, as Alzahrani and Daim (2019a) showed that investment opportunity and recognition by businesses are two major factors that drive cryptocurrency adoption, which are two sub-indicators of economic factors. This is also largely in line withBohr and Bashir's (2014) finding that lack of trust in the banking system is the main reason for cryptocurrency adoption, as acting as an alternative to the banking system is a sub-indicator under the economic factors of this study. Moreover, Sylvie & Pascal(2020), also in a previous study found that people adopt cryptocurrency to make profits and use as an investment vehicle. The top factor driving cryptocurrency adoption in Alzahrani and Daim's (2019a) study is investment opportunity, which is a major economic factor, as the statutory currency loses its value due to high levels of inflation in the country at the time of this study.

This study also found that social factors have a significant and significant effect on cryptocurrency adoption in Sri Lanka. Social factors include sub-indicators, such as subjective norms, global attention, and influencers' involvement. Overall, social factors were found to significantly affect cryptocurrency adoption, which is consistent with the findings of Alzahrani and Daim (2019a). Their study concluded that subjective norms and global attention are two major factors that influence cryptocurrency adoption decisions. The significance of subjective norms shows that more users tend to adopt cryptocurrency if their peers influence them to do the same, while rising global attention and influencer involvement also shows how users are influenced by popular culture to adopt novel technologies.

As per the findings of this study, personal factors, including technological curiosity, full control over one's money, and privacy, do not have a large effect on cryptocurrency adoption in Sri Lanka. This contradicts with the findings of Alzahrani & Daim (2019a) who found privacy which is under personal factors to be one of the main driving factors of cryptocurrency adoption. Interestingly, personal factors have a negative effect on cryptocurrency adoption. This implies that investors who are highly concerned with technological curiosity, full control over money, and privacy are less motivated to invest in cryptocurrency. Since the majority of the study respondents were young investors, representing ages below 35 years, this result might not be staggered. Young investors are more interested in the technical aspects leading to low technology curiosity and spending considerable time on social media, leading to fewer privacy concerns. On these notes, personal factors might have negative variation in cryptocurrency adoption decisions; hence, this becomes a skeptical view, and further examination is required.

Heuristic-driven biases refer to how investors have a bias concerning the likelihood of uncertain events that will affect how they think and make decisions. In other words, investors can use the rule of thumb when making decisions in uncertain and complex situations, which could lead to mistakes in such decisions. This study attempted to ascertain the influence these heuristic-driven biases could have on the cryptocurrency adoption decisions of Sri Lankan investors, finding that heuristic-driven biases have a large effect on cryptocurrency adoption, bringing about a 48% negative variation in cryptocurrency adoption decisions. Accordingly, investors underlining their investment decisions primarily on one piece of information that is first acquired from the surrounding environment are less motivated to invest in cryptocurrency.As mentioned above, since the majority of the respondents were young investors, they might not be so fearful of losses and may not try to avoid a loss more so than on making gains. Most likely, young investors may not tend to feel more stressed by potential losses and are more prudent to invest in high-risk investments. The potential reason for this negative variation needs to be further examined. While previous studies on behavioral biases connected to the cryptocurrency market are limited, Al-Mansour's(2020)study, which analyzed the effect of heuristics, herding, and prospect on investors' investment decisions in the cryptocurrency market, found that all three have a significant effect. Therefore, the findings of this study are consistent with those of the previous studies.

Frame-dependent bias occurs when investors' decisions are biased, depending on how information is framed or how data and information are presented. The study revealed that the effect of frame-dependent bias on cryptocurrency adoption is large and that this bias brings about 54% positive variations in cryptocurrency adoption decisions. Similar to heuristic-driven biases, past studies on cryptocurrency adoption and frame-dependent bias are limited. However, these findings are consistent with the available literature, as Craggs(2016) also found framing bias among cryptocurrency investors worldwide. The results reveal that investors are usually more sensitive to negative frames than positive ones, and their decisions are framed based on limited information.

Implications and Conclusion

From a theoretical perspective, this study contributes to the existing body of literature in numerous ways. First, the findings of this study contribute to the growing literature on cryptocurrency investors, a field seldom explored in the Sri Lankan context. In line with similar studies conducted in other geographical contexts, the majority of Sri Lankan cryptocurrency investors are males of younger age groups with relatively high levels of educational qualifications. Second, the study provides greater insight into the factors affecting cryptocurrency adoption decisions of Sri Lankan investors. This study found that technical, social, and economic factors have a large effect on the decision to adopt cryptocurrency. Third, this study extends the literature on the influence of behavioral biases on cryptocurrency investment decisions. Prior studies have mainly focused on the presence of behavioral biases among investors, and very few attempts have been made to investigate the influence of behavioral biases on cryptocurrency investment decisions. In this regard, the study revealed that heuristic-driven biases have a significant, large, negative variation in cryptocurrency investment decisions, while framing bias has a large, positive effect on the cryptocurrency investment decisions of Sri Lankan cryptocurrency traders.

From a practical perspective, the implications of the findings of this study are significant. The study identified ten main demographic characteristics of Sri Lankan cryptocurrency investors, which provides a clear idea of the specific groups of people who are more likely to adopt novel, upcoming technologies and investment tools. This knowledge will be helpful to regulatory bodies in developing a legal framework covering cryptocurrencies to fine-tune the rules and regulations for these demographic groups. Moreover, the findings of this study concerning the adoption motivators and the influence of biases on investment decisions will help investors better articulate their investment decisions in the cryptocurrency market with more knowledge of the behavioral finance perspective on how biases affect their decisions.As a country, Sri Lanka should be more receptive to the new developments that are happening around the world. With the current phase and acceleration of globalization, the world is becoming increasingly interconnected, and financial systems may evolve. Most developed countries have identified the opportunities and dangers presented by cryptocurrencies and are in the process of developing frameworks to incorporate the evolving use of these digital financial assets within their economies. While some lawmakers have mentioned this and the intention of the government to develop such a framework, it has not yet been implemented. Sri Lanka should ensure that it does not fall behind its peers in embracing new technological changes related to money, if it aims to become a financial hub in the region.

From a behavioral bias perspective, biases lead to irrational decisions, which can potentially cause losses (Talwar*et al*., 2021). By uncovering the effect and relative importance of heuristic-driven biases influencing investment decisions in cryptocurrencies, this study provides useful information for firms offering investment advisory services to such investors. Knowing the effect of heuristic-driven biases on investors' decisions can help firms offer advice in line with their information-seeking behavior, risk appetite, and management. Moreover, the confirmation of the existence of heuristic-driven biases among young investors indicates a need for investor education efforts directed towards this generation to reduce investment in high-risk investments. From the perspective of frame-dependent biases, investors are required to guide and train investors to make investment-related decisions as rationally as possible. As Thaler (1985) andFrensidy (2016) claim, investorsdo not consider interactions among multiple decisions and give more weight to the information that comes first. In this regard, the findings of this study can help firms and academics engage in investor education and training to analyze data in a dynamic environment, accumulate learning based on the investigation of dynamic factors, and make them appreciate the benefits of diversification.

The contribution of our study must be evaluated in light of some limitations. The study focused on a narrow sample based on purposive sample that might restrict the generalizability of the findings to a broader population. Future research can expand the findings of our study by testing a larger sample. The study used a structured questionnaire that did not include open-ended questions for data collection. Therefore, for a much deeper understanding, especially of the reasons for using cryptocurrencies, a more detailed study could be conducted using an interview method to gain an in-depth understanding of why and how users entered the cryptocurrency world. The study selected a set of biases to represent the categories proposed by Shefrin (2000): heuristic-driven and frame-dependent biases.Furthermore, future research can test biases, such as mood and cognitive and emotional biases, by referring to Pompian (2006; 2012), self- deception, heuristic simplification, social interaction by Montier (2002), and other classifications.Additionally, there are numerous future research opportunities in this area; such as assessing the challenges faced by governments in developing a legal framework for cryptocurrencies, factors affecting people's perception of cryptocurrencies, cybercrime and cryptocurrencies, economic development and cryptocurrencies etc., available for the future researchers.Especially in the developing country, Asian country, and Sri Lankan context, there is much to be discovered and studied regarding cryptocurrencies.

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