Journal of
Organisational Studies and Innovation
Vol. 9, no4, Winter 2022

Psychological and Social Factors Determining Investment Decisions in Cryptocurrency: Exploring the Mediating Role of Cognitive Biases

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Received: Sep 25, 2021; Revised: April 3, 2022; Accepted: Nov 25, 2022

Abstract: This empirical research investigates whether investment decisions of cryptocurrency investors in Pakistan are influenced by a set of cognitive biases, as propagated by the theories in behavioural finance. To fill a dearth in the existing literature, this study evaluates the psychological and social sources of the cognitive biases that in turn affect investment decisions in cryptocurrency, therefore, this research essentially examines the mediating role of cognitive biases (Herding, Overconfidence, Representativeness, and Self-serving biases) between the linkages of socio-psychological factors (Money Anxiety, Social Interactions, Stress and Internal Locus of Control) and investment decisions in cryptocurrencies. Sample size of 313 respondents has been used, employing snowball sampling method, to analyze the data using Partial Least Square Structural Equation Modeling. The results reveal that herding bias, overconfidence bias and representativeness bias partially mediate the relationship between money anxiety, social interactions, stress and investment decisions in cryptocurrencies whereas self-serving bias fails to exert any mediation effect between internal locus of control and investment decisions. The results reveal that money anxiety causes herding bias which, in turn, affects the investment decisions in cryptocurrency positively; Stress leads to representativeness bias which, in turn, undermines investment decisions in cryptocurrency and social interactions generate overconfidence bias which, in turn, affects the investment decisions negatively.
Keywords: *Cognitive Biases; Investment Decisions; Cryptocurrency; Psychological and Social Factors; Herding Bias; Representativeness Bias; Overconfidence Bias; Self-Serving Bias.*

Introduction

Investors who make investment decisions based on a thorough fundamental study of the assets in question and optimize their risk-return profile are said to be rationalists in investment decisions because they are more likely to get the most out of their investments (Markowitz, 1952). Behavioural finance, on the other hand, promotes the notion that investors rarely operate logically and are easily swayed by biases, resulting in illogical behaviour, in order to make hasty decisions without conducting the full due research (Shefrin and Statman, 2011). One of the key causes of inefficient capital markets is cognitive biases. Prudent investment analysis necessitates a set of abilities and information that a beginner investor generally lacks, and as a result, investors are susceptible to mental shortcuts influenced by their behavioural or cognitive biases. Therefore, investors inevitably end up making irrational decisions due to their psychological, emotional and social biases (Rubinstein, 2001). Traditional finance theories

[1] https://doi.org/10.51659/josi.22.159

such as, Capital Asset Pricing Model, Efficient Market Hypothesis, and Modern Portfolio Theory all assume that investors act rationally and in a risk-averse manner, taking into consideration all relevant aspects and doing a thorough risk-return analysis; However, the unsound behaviour displayed by investors in practice, as evidenced by the literature, is at odds with the traditional ideas taught at universities. Behavioural finance theory can help people understand how and why behavioural biases influence investing decisions and the motives behind them (Subrahmanyam, 2008). Various research, mostly in developed countries, have been undertaken to determine which specific biases influence investing decisions, with mixed results for each category of cognitive bias. For instance, according to Ariely et al., (2006), calculating the intrinsic value of securities is a difficult task, thus investors employ mental accounting techniques to evaluate assets. Individual decisions are the outcome of a complex process in which an individual's brain system conducts several interconnected functions that may or may not be consistent with classical financial theorists' assumptions. An investor's weak or negative emotional state can lead to poor financial decisions. Negative emotions, according to research, have a greater impact on financial decision-making than good emotions because they produce personality disorders (Zaki and Ochsner, 2012; Cheng, 2019; Druckman and McDermott, 2008). Previous studies have used psychological theories such as attentional control theory and processing efficiency theory to explain people's cognitive behaviour (Eysenck et al., 2007). Meanwhile, the effect of behavioural biases on financial decision-making was explained using prospect theory.

This research adds to the existing body of knowledge in a variety of ways: It begins by explaining how cognitive biases influence investment decisions in cryptocurrency. Secondly, it investigates the most common causes of cognitive biases. Thirdly, it clarifies the importance of cognitive biases as mediating factors. Finally, it discusses how psychological elements (stress, locus of control, and anxiety) as well as social interaction influence investment decisions directly and indirectly in the context of investments in cryptocurrencies in Pakistan.

Investment in cryptocurrency has remained controversial since its inception more than a decade ago because of its eccentric nature and perhaps that is the reason why it has been a topic of interest for academia and investors alike. In the last few years, researchers have substantially endeavoured in this area to explore its potential implications in the investment arena. Through the lens of behavioural economics, Aloosh and Ouzan (2020) examined the dynamics of cryptocurrency pricing and concluded that participants in the cryptocurrency market appear to be acting irrationally. This study showed that the cryptocurrency market has a strong small price bias, which supports the concept that investors react to news differently depending on the price level. Low-priced cryptocurrencies are far more volatile than their high-priced counterparts, according to the study. Gurdgiev and Loughlin (2020) investigated how the combination between behavioural factors influencing investor decisions and publicly available data flows affects cryptocurrency price dynamics. The findings revealed that investors' emotions can predict the price direction of cryptocurrencies, showing that herding and anchoring biases have a direct impact. Cryptocurrency markets, according to Mnif, Jarboui, and Mouakhar (2020), are complex systems built on speculation in which investors interact using tactics that induce some biases that cause endogenous instability. During the COVID-19 outbreak, this paper studied herding biases by calculating the self-similarity intensity of bitcoin returns. COVID-19 has a beneficial impact on bitcoin market efficiency, according to the empirical findings. The impact of investor attitude on bitcoin returns was investigated by Anamika, Chakraborty and Subramaniam (2021). The study's findings revealed that when investors are bullish about Bitcoin, the price of Bitcoin rises. After controlling for the essential parameters, Bitcoin sentiment has a large amount of power in predicting Bitcoin prices. When investors in the stock market are bearish, bitcoin values climb, demonstrating that

cryptocurrency can be used as an alternative investment vehicle. After accounting for potential influences on bitcoin prices, the findings remain unaltered.
Investment in cryptocurrency is currently considered to be one of the most speculative investments because of its peculiar price volatility and there appears to be a widespread lack of understanding on the part of investors with respect to the mechanism behind the price movements of the currencies. Nevertheless, investors all over the world seem to be overenthusiastically investing in cryptocurrency while indulging in hefty risk taking. This eccentric attitude of investors generates a curiosity amongst researchers in the field of behavioural finance as to what socio-psychological factors trigger the cognitive biases among investors which, in turn, affect the investment decisions in cryptocurrencies. Identification of the underlying factors causing cognitive biases can make investors aware of the sources behind their biased decisions resulting in adverse investment outcomes so that they do not fall prey to the biases and make investment decisions in a rational manner.
Previous studies on the similar topic have focused on investigating the effects of cognitive/behavioural biases on investment decisions or the role of biases as mediators only in the context of stock investments (Jabeen et al., 2020; Khan et al., 2017) whereas this study focuses on investment decisions in cryptocurrency which is pretty much an unexplored area with respect to the chosen topic and therefore an empirical study on this topic is warranted so that the factors affecting investment decisions in cryptocurrency can be identified and the investors could benefit from the findings. Moreover, there is a dearth of studies in the existing literature that investigates the role of cognitive biases as mediators to evaluate the impact of socio-psychological factors on investment decisions in cryptocurrencies so as to identify the underlying factors causing cognitive biases which, in turn, impede decision making as per the theories of behavioural finance. Therefore, this study attempts to achieve following research objectives: (i) To determine the mediating effect of herding bias on the relationship between money anxiety and investment decisions in cryptocurrency; (ii) To determine the mediating effect of representativeness bias on the relationship between stress and investment decisions in cryptocurrency; (iii) To determine the mediating effect of overconfidence bias on the relationship between social interactions and investment decisions in cryptocurrency; (iv) To determine the mediating effect of self-serving bias on the relationship between internal locus of control and investment decisions in cryptocurrency

Literature Review and Theoretical Underpinnings

Fromlet (2001) states that investor behaviour is a subset of behaviour finance, which aims to explain and anticipate the systematic financial market consequences of psychological decision-making processes. Individual behaviour and market phenomena are strongly linked in behaviour finance, which draws on information from both the psychological and financial fields. Behavioural finance has had a significant role to play in shaping the decision making of investors in the capital markets. Behavioural biases, as defined by behavioural finance theory, can be blamed for a large part of the irrational behaviour that led to the financial crisis of 2007-2008, which began in the United States and spread globally (Szyszka, 2010). Previous research has indicated that when investors' psychological, social, and emotional biases come into play while making investing decisions, they suffer significant losses in the capital markets (Gervais and Odean, 2001; Odean et al., 1998).
In behavioural finance, heuristics theory refers to investors' proclivity to use mental shortcuts or rules of thumb while making investing decisions. When time is limited, heuristics can assist in making quick decisions, but they can also lead to biased decisions that lack rigorous investigation. Representativeness bias, availability bias, anchoring and adjustment bias are among the most common heuristics (Tversky and Kahneman, 1974; Ritter, 2003).
Humans have a natural tendency to gamble with earnings rather than losses, according to the prospect theory in behavioural finance. Losses and gains are viewed differently, according to

the theory, since people make decisions based on perceived gains rather than actual losses. The theory's basic premise is that if a person is given two similar options, one with potential benefits and the other with potential costs, he or she will choose the former. People are more emotionally affected by losses than gains, thus if given two options with the same outcome, they will choose the one that provides perceived rewards. According to the theory, the certainty effect occurs when people prefer certain outcomes over the ones that are only plausible. The certainty effect causes people to avoid taking risks when there is a chance of a certain payoff. It also pushes people to seek out danger when the alternative is a guaranteed loss. The isolation effect occurs when people are given two options with the same result but distinct approaches to that result. In this case, people will likely cancel out similar knowledge to minimize cognitive burden, and their decisions may vary depending on how the options are worded (Kahneman and Tversky, 1979).

The efficient market hypothesis (EMH), often known as the efficient market theory, claims that stock prices reflect all available information and that continuously achieving a higher return is unlikely. According to the Efficient Market Theory, equities trade at their fair value on exchanges, making it difficult for investors to buy cheap stocks or sell for inflated prices. As a result, beating the overall market with skilled stock selection or market timing should be tough, and the only way an investor can achieve superior returns is to buy riskier stocks (Sharpe, 1970). People are "rational" in traditional finance, but "normal" in behavioural finance. Rational people prefer utilitarian features to value-expressive ones, are never perplexed by cognitive errors, have perfect self-control, are often risk averse, and never regret their decisions. Normal people do not follow such pattern. Standard finance expects too much when it comes to market efficiency in the rational sense, and investment practitioners ask too much when they insist that behavioural finance's core contribution is to help beat the market. Accepting market efficiency in the context of outperforming the market while rejecting it in the sense of rationality would inspire finance academics to inquire about investment professionals' viewpoints beyond outperforming the market. Investment professionals come from a variety of backgrounds, and we must consider both utilitarian and value expressive advantages (Chuvakhin, 2001).

Hypotheses Development

The role of cognitive biases in making investment decisions and investment performance in cryptocurrency is investigated in two manners in this study: The direct effect of cognitive biases on investment performance is examined and the mediating role of biases is assessed to determine the social and psychological factors as the source of the cognitive biases since this study hypothesizes that there are socio-psychological factors responsible in the generation and manifestation of cognitive biases..

Money anxiety, Herding Bias and Investment Decisions

An individual in a state of anxiety is unable to initiate a distinct behavioural pattern and is unable to eliminate or change the event, object, or judgment that is undermining the intended aim. Anxiety has a negative impact on cognitive performance, hence it is extremely important in the field of cognition. (Derakshan and Eysenck, 2009; Zimbardo and Boyd, 2015). Anxiety, according to attentional control theory, diminishes attentional control, which reduces processing efficiency. As a result, there's a chance that processing resources will be misdirected away from task-relevant stimuli and toward non-task-relevant stimuli. An anxious person's judgements and decisions are influenced by the qualities of their feelings; as a result, an anxious person becomes uncertain and loses control over an outcome. At the same time, uncertainty erodes self-confidence through reducing general self-efficacy, or the idea that one is capable of achieving a specified, desirable goal (Kraft et al., 2021; Franklin, Smith and Holmes, 2015). Low certainty and low control both imply the need to reduce uncertainty and increase control. As a result, anxious people will favour solutions that would lower their anxiety and provide them more control by using various methods. Strengthening social interactions is one way to reduce uncertainty and gain control. The other is to develop confidence and lessen uncertainty by following the actions and opinions of others. People who are depressed give others' opinions more weight than their own (Newsom, Shaw, August, and Strath, 2018; Galatzer-Levy, Nickerson, Litz, and Marmar, 2013).

The existing literature proposes that investors follow the crowd in order to make a wise judgement; if a big group of investors invests in a specific project, the rest of the investors will follow suit. In contrast, if some investors pull out of a project, the rest of the group will pull out as well, even though no one has suffered losses (Yao, Ma and He, 2014; Joyce and Nabar, 2009). Hence, this study also attempts to further validate the hypothesis that investors suffering from anxiety tend to herd more than those who are more emotionally stable in the context of investments in cryptocurrency.

Hypothesis 1 (H1): Money anxiety causes herding bias which, in turn, affects the investment decisions in cryptocurrencies negatively.

Stress, Representativeness Bias and Investment Decisions

Existing literature amply implies that stressed individuals have tendencies to be representatively biased. A sense of pressure and tension is referred to as stress. The majority of the research has centered on the idea that stress impairs a person's environmental scan, or capacity to detect and understand potential risks in their environment. Stress limits the range of attended signals; also, one's perceptual field narrows, and the scope of behavior is limited to the elements that contribute the most to the current behavior direction (Bratman et al., 2015; LeBlanc, McConnell and Monteiro, 2015). People frequently have erroneous perceptions regarding the likelihood of events. Stress reduces the amount of attention given to information processing, which decreases cognitive performance. People believe that a random sample drawn from the population is a true reflection of the entire population and is impartial because of the law of small numbers. This idea is often valid in the case of big, unbiased independent samples. The inference drawn from this sample will be biased if the sample is not representative of the population and is invalid due to its insufficient size; this idea can be explained using the representativeness heuristic cognitive bias. People often assume that sample statistics estimates are equal to population parameters, which is a dangerous assumption that can easily lead to an inaccurate prediction. (Kahneman and Tversky, 1979; Rabin, 2002; Newell, Lagnado and Shanks, 2015).

Hence, based on the existing literature, it is hypothesized that stressed individuals are more prone to falling prey to representativeness bias which leads to irrational investment decisions.

Hypothesis 2 (H2): Stress leads to representativeness bias which, in turn, undermines investment decisions in cryptocurrencies.

Social Interaction, Overconfidence Bias and Investment Decisions

Investment decisions are rarely made without the influence of social interactions. Investors have tendencies to talk to their social counterpart, peers and people in their social circle about their investment choices. Investment decision, therefore, are not made in a vacuum and are result of how we are affected by our day-to-day interactions with people in our homes, offices, social circles and on the various platforms in the social media as well. Investors prefer to invest on their own, but they also require the psychological support of those who share their goals. Since the emergence of the Internet and digital communications technologies, changes in how people communicate with one another have profoundly changed the buying and selling activities of investors. As a result, we may claim that social interaction influences an investor's decision and that an investor learns from other people's interactions (Tanner et al., 2008; Dunfee, 2003; Barom, 2019). Overconfidence drives investors to overestimate their knowledge and undervalue dangers, according to psychology. Some investors believe they have substantial or insider information that will provide them an advantage over other investors, and as a result, they become overconfident in their investing selections (Park et al., 2010)

Overconfident investors will be unable to gauge profit potential and may overlook transaction costs. Because the overconfident investor is too certain of his opinions, it increases trading frequency. For some investors, information overload without competent analysis leads to dangerous decision-making. Overconfidence is a form of deception that can lead to skewed investing decisions. As a result, social engagement leads to overconfidence, which has a negative impact on investment decisions (Rabbani et al., 2018; Barber, Lee, Liu, and Odean, 2008; Trinugroho and Sembel, 2011). Hence this study hypothesizes as follows:

Hypothesis 3 (H3): Social interactions generate overconfidence bias which, in turn, affects the investment decisions negatively.

Internal Locus of Control, Self-Serving Bias and Investment Decisions

Any cognitive or perceptual process that is warped by the drive to maintain and promote self-esteem is referred to as a self-serving bias. Individuals who dismiss the validity of negative comments, focus on their strengths and accomplishments while ignoring their flaws and failings, or accept more responsibility for their group's work than they give to other members are defending their egos from harm. These cognitive and perceptual tendencies not only perpetuate illusions and mistakes, but they also satisfy the self-esteem needs. Individuals with an external locus of control believe that circumstances beyond their control are responsible for both positive and negative outcomes, whereas those with an internal locus of control believe that they are personally accountable for their outcomes. (Forsyth, 2008; Rotter, 1966)

The individual inclination for people to believe that events in their life are due to their input (internal) or are dependent on external sources (external) is known as locus of control. The self-serving bias refers to people's tendency to claim credit for their accomplishments while denying responsibility for their shortcomings. There were no gender differences in the dimensions of locus of control or self-serving bias, according to the findings. The hypothesis that internal people would attribute the causes of outcomes in a manner compatible with their locus of control received little support (Greenfield, 2000). Campbell and Sedikides (1999) proposed that the self-serving bias was seen in participants who had both an external and internal locus of control. Participants with an external locus of control, on the other hand, amplified the self-serving bias, a trend that supports the self-threat paradigm. Lather, Jain and Anand (2020) examined the relationship between locus of control and behavioral biases (emotional and cognitive) in the context of investment decision making. The study found significant linkages between locus of control and cognitive biases. The findings of this study helped researchers better understand the impact of locus of control on investor biases and preferences, making it easier to identify an investor's proclivity for certain types of investments. This also serves as a technique for determining whether investors have an underlying proclivity for various investment biases.

The existing literature suggests mixed opinions as to the specific impact of internal/external locus of control on self-serving bias in individuals in making investment decisions. In this regard, this study, however, hypothesizes as follows:

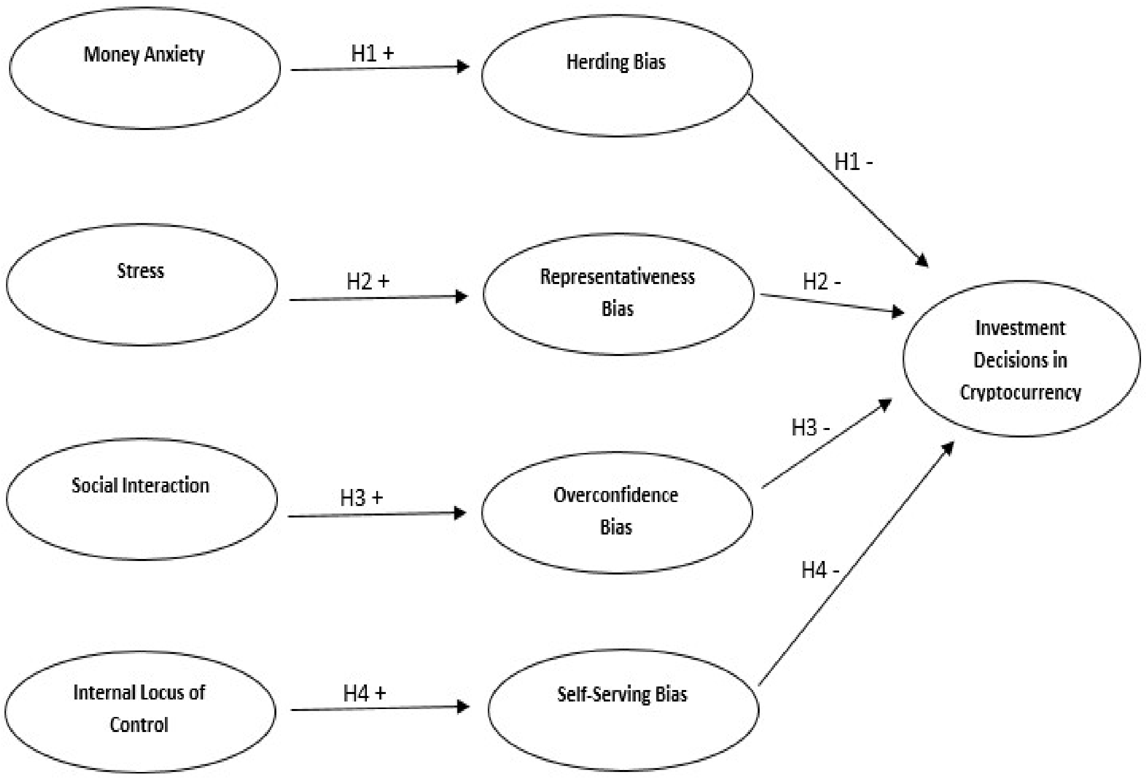
Hypothesis 4 (H4): Internal locus of control generates self-serving bias which, in turn, damages the quality of investment decisions.

Methodology

Research Philosophy, Design and Approach

Since a scientific approach was used to test hypotheses and assess results without any personal value judgments or researcher bias, the underlying research philosophy and ontological viewpoint that derives this research is positivism. Deductive approach has been used and the research design is entirely quantitative because theories under the ambit of behavioral finance, psychology and sociology have been tested, such as, prospect theory, heuristic theory, efficient market theory, cognitive theory of depression and attentional control theory using quantitative data analysis techniques. The study can be termed explanatory and to some extent exploratory as well because of the aspect of exploring the effects of socio-psychological factors on investment decisions in the context of cryptocurrencies

Figure 1. Conceptualized Framework



Data Source and Population of the Study

This research uses primary data since the research objectives require primary data from respondents who are actively investing in cryptocurrencies in order to examine the effect of socio-psychological factors on their investment decisions while assessing the mediating impact of cognitive biases, therefore, cryptocurrencies investors in Pakistan comprise the population of the study. Investment in cryptocurrency in Pakistan is not regulated by the government or any regulatory body, therefore, it is very difficult to cite an exact number of crypto-investors in Pakistan or to gather information about investors from any exchange, however, there are numerous groups on the social media in which investors discus their investment decisions with each other. Therefore, this study traces cryptocurrency investors through various social media groups on the internet. Moreover, investors were identified in the local community through friends and family and they were requested to give leads to other investors.

Sampling Strategy and Sample Size

Non-probability sampling method, i.e. snowball sampling has been used in this study to draw a representative sample and collect the required data due to the scattered nature and inexact quantity of the population wherein a total of 500 questionnaires were initially administered to investors and traders of cryptocurrencies, such as Bitcoin, Ethereum, Thether, etc. in Pakistan, mainly in the cities of Karachi (the largest city and the financial hub of Pakistan) and Hyderabad. Out of 500 questionnaires served, the response rate was 65%, i.e. 325. Missing values were handled with mean imputation method, however, respondents with missing values of more than 10 percent were deleted so as to ensure that the statistical analysis is without any bias (Bennett, 2001). After deleting responses of such respondents, cleaning the data and handling missing values, 313 responses were spared for data analysis. Scholars have varied viewpoints on the sample size for a quantitative study. Sample of 250 has been prescribed to be appropriate for a quantitative study by some scholars and on the other hand, confidence interval and confidence level can be the basis to select the sample size. It is also proposed that the number of respondents should be 10 times the number of items used in the scale. (Hair, Black, Babin and Anderson, 2010). Sekaran (2000) recommends that for multivariate data analysis, a minimum of 30 respondents per variable should be selected. In the questionnaire adapted, there are 31 questions covering all the constructs used in the study, therefore, the sample size should not be less than 310, i.e. 31 times 10. This study, therefore, having a sample size of 313 is statistically justified. In order to have a representative sample of the population, the questionnaire was administered to those who are practically investors in cryptocurrency and in order to ensure this, a filter question was added at the start of the questionnaire.

Research Variables

This research employs nine constructs in order to achieve the desired research objectives. There are four socio-psychological constructs used in the study which act as independent variables in the model (see figure 1), namely, money anxiety, stress, social interaction and internal locus of control. As mediators, this study uses four constructs (herding bias, representativeness bias, overconfidence bias and self-serving bias) which are the cognitive biases derived from the theories in behavioral finance. Investment decisions in cryptocurrencies is used the dependent variable in the model. The description of all constructs is given in the literature review section

Research Instrument and Items

The study uses a structured questionnaire with five-point Likert scale to collect data. The items in the questionnaire have been adapted from various studies as follows:

Table 1. Sources of adapted items in the questionnaire

Construct	No. of Items/Questions	Source
Money Anxiety	4	(Lim and Sng, 2006)
Stress	4	(Mitchell, Crane, and Kim, 2008).
Social Interaction	3	(Ragins and Cotton, 1999)
Internal Locus of Control	4	(Craig, Franklin and Andrews, 1984)
Herding Bias	3	(Kimani, 2018)
Representativeness Bias	3	(Khan et al., 2017)
Overconfidence Bias	3	(Kimani, 2018)
Self-Serving Bias	4	(Campbell and Sedikides, 1999)
Investment Decisions in Cryptocurrencies	3	(Jabeen et al., 2020)

Data Analysis

The present study has used partial least square structural equation modelling (PLS-SEM) with the help of SmartPLS 3.2 as a main tool for data analysis. PLS-SEM is a multi-level regression technique designed to improve predictive accuracy of estimates and to account for explained variance in the endogenous constructs. Moreover, for studies that are predictive in their pursuit, PLS-SEM is an appropriate tool (Hair, Ringle and Sarstedt, 2011). Therefore, PLS-SEM was deemed to be an appropriate option for this study to run the model and test hypotheses on the collected data. However, in order to perform descriptive analysis on the demographics, SPPS version 25 was used.

Results and Discussion

Demographic Profile of Investors

Table 2 given below depicts the demographic profile of the respondents. Out of 313 respondents in the final sample, 83.4% were males whereas 16.6% were females which is understandable considering the reduced tendencies of females to invest in cryptocurrencies in Pakistan. However, 16.6% for females is still a significant number because the study mainly focused on big cities, such as, Karachi where the ratio of educated females is higher. 83.4% of respondents fall in the age bracket of 26-35 years which is an indication that a considerable portion of youth is investing in cryptocurrencies in Pakistan and moreover people of this age bracket are financially independent as well. 8.3% of respondents are 25 years or below because the questionnaire was also sent to university students who invest in cryptocurrencies because of the accessibility convenience. Respondents of various education levels are part of this study. The highest number is bachelor degree holders (58.5%) followed by master or above degree holders (33.2%). 91.7% of respondents were investing their own money in cryptocurrencies whereas 8.3% were investing on behalf of their clients.

Table 2. Sample Demographics

Demographic	Sub-Groups	Frequency	% Frequency	Cumulative % Frequency
Sex	Female	52	16.6	16.6
	Male	261	83.4	100.0
	Total	313	100.0	
Age	25 years or below	26	8.3	8.3
	26 - 35 years	261	83.4	91.7
	36 - 45 years	26	8.3	100.0
	46 - 55 years	0	0	-
	More than 55 years	0	0	-
	Total	313	100	
Level of Education	Bachelors	183	58.5	58.5
	Diploma	26	8.3	66.8
	Intermediate / A Level	0	0	-
	Masters or above	104	33.2	100.0
	Total	313	100.0	
	Both	0	0	-

Your decision to invest in stocks applies to:	Your clients (Other people's money)	26	8.3	8.3
	Yourself (Your own money)	287	91.7	100.0
	Total	313	100.0	

Descriptive Statistics

Table 3 given below summarizes the descriptive statistics on the data for all constructs, including sample mean values, standard deviation, skewness and kurtosis. Univariate normality of the collected data is verified through the values of skewness and kurtosis. Since all value lie within the range of +2 to -2, data can be said to have approximately normal distribution (Mallery, 2003). Mean values of all socio-psychological constructs (Money Anxiety, Stress, Social Interaction and Internal Locus of Control) are greater than 3 which is an indication that investors by and large possess the dispositions to be affected by these factors as per the coding convention used in the Likert scale. All cognitive biases also have mean values greater than 3 which shows that investors, on average, fall prey to the cognitive biases (Herding, Representativeness, Overconfidence and Self-Serving) used in the study. Investment decisions having mean values less than 3 shows that the outcome of investment decisions have been less than satisfactory for investors on average.

Table 3. Descriptive Statistics

Construct	Mean	Standard Deviation	Skewness	Kurtosis
Money Anxiety	3.13	0.96	-0.534	-0.889
Stress	3.25	0.93	-0.142	-1.327
Social Interaction	3.36	1.10	-0.449	-0.867
Internal Locus of Control	3.17	1.11	-0.445	-1.293
Herding Bias	3.30	1.12	-0.605	-0.785
Representativeness Bias	3.21	1.06	-0.273	-0.999
Overconfidence Bias	3.20	0.97	-0.432	-0.582
Self-Serving Bias	3.23	0.98	-0.336	-0.758
Investment Decisions in Cryptocurrency	2.68	1.24	0.479	-1.335

Measurement Reliability and Validity of Data

In order to ascertain internal consistency of the items, composite reliability and Cronbach's alpha tests were applied whereas average variance extracted was employed to gauge the validity of the instrument, i.e. whether it measure the constructs it intends to measure (Carmines and Zeller, 1979; Valentini and Damasio, 2016). As depicted in table 4 given below, the measures for reliability and validity of the constructs satisfy the minimum acceptable cut-off values, i.e. 0.7 for Cronbach's alpha and composite reliability and 0.5 for average variance extracted (Hair et al., 2014; Peterson and Kim, 2013). Therefore, it can be inferred that the measurement reliability and validity has been sustained in the data as per the requirement for further analysis in the structural model.

Table 4. Measurement Reliability and Validity of Data

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Money Anxiety	0.880	0.918	0.737
Stress	0.837	0.867	0.622
Social Interaction	0.856	0.910	0.772
Internal Locus of Control	0.915	0.940	0.796
Herding Bias	0.878	0.924	0.802
Representativeness Bias	0.868	0.914	0.781
Overconfidence Bias	0.855	0.911	0.774
Self-Serving Bias	0.852	0.906	0.715
Investment Decisions in Cryptocurrency	0.923	0.951	0.867

Discriminant Validity

In order to assess whether the constructs used in the study possess uniqueness, i.e. each construct is distinct from all other constructs, discriminant validity has been tested using Fornell-Locker criterion. The square root of total variance explained, which must be greater than the value of each pair of correlations, is calculated in the discriminant validity test (Fornell and Larcker, 1981; Ab Hamid et al., 2017; Henseler, Ringle and Sarstedt, 2015). Tables 5 indicates that the discriminant validity for all constructs used in this study is achieved.

Table 5. Fornell-Locker Criterion

	Herding	Int. Loc. of Con	Inv. Dec.	Mon. Anx.	Overconf.	Repre.	Self-Ser.	Soc. Int.	Stress
Herding	0.895								
Int. Loc. of Con.	0.415	0.892							
Inv. Dec.	-0.009	-0.549	0.931						
Mon. Anx.	0.266	0.626	-0.630	0.859					
Overconf.	0.297	0.415	-0.470	0.140	0.880				
Repre.	0.408	0.627	-0.454	0.467	0.464	0.884			
Self-Ser.	0.522	0.770	-0.391	0.523	0.450	0.797	0.845		
Soc. Int.	0.058	0.414	-0.587	0.435	0.421	0.384	0.286	0.878	
Stress	0.550	0.458	-0.444	0.514	0.516	0.304	0.523	0.340	0.789

Indicator Reliability: Factor Loadings

The outer loading measures are computed to evaluate the number of items that can be kept or removed from the scale that are not causing any additional variance and to test the validity of the outer model. The minimum acceptable loading value for an item to be retained is 0.5 (Hair et al., 2014). As depicted in the table 6 below, the outer loadings of all items used to measure the independent and dependent variables are more than 0.5, therefore all these items have been retained in the model.

Table 6. Outer Loadings

Items	Outer Loadings
Herding1	0.877
Herding2	0.914
Herding3	0.896
IntLocus1	0.924
IntLocus2	0.870
IntLocus3	0.888
IntLocus4	0.888
MonAnx1	0.917
MonAnx2	0.932
MonAnx3	0.787
MonAnx4	0.786
OverConf1	0.870
OverConf2	0.901
OverConf3	0.868
Repre1	0.903
Repre2	0.833
Repre3	0.913
SelfServ1	0.918
SelfServ2	0.915
SelfServ3	0.942
SelfServ4	0.539
SocInt1	0.861
SocInt2	0.930
SocInt3	0.842
Stress1	0.672
Stress2	0.740
Stress3	0.869
Stress4	0.857
InvDec1	0.946
InvDec2	0.918
InvDec3	0.929

Common Method Bias

Common method bias (CMB) occurs when the instrument produces variability in replies rather than the true predispositions of the respondents that the instrument is aiming to disclose. In other words, the instrument introduces a bias, which is then analyzed through variances. As a result, the noise from the biased instruments pollutes the results obtained. CMB can be tested using Harman's single factor score; the total variance for a single factor should be less than 50% in order to deny the existence of CMB in the data (Podsakoff et al., 2003). In this study, the same questionnaire was used to collect data within the same time frame; Moreover, research design was purely cross-sectional. Therefore, the possibility of common method bias (CMB) existed. We used Harman's single factor technique to check for the presence of CMB in the data by loading all items, measuring latent variables, into one common factor. The first factor in the output showed variance below 50%, therefore, the data is free from CMB.

Mediation Analysis Results – Hypotheses Testing

Mediation analysis was performed to evaluate the mediating role of cognitive biases (Herding, representativeness, overconfidence and self-serving) on the linkage between socio-psychological factors (Money anxiety, stress, social interaction and internal locus of control) and investment decisions in cryptocurrencies. Table 7a, 7b and 7c reveal the overall mediation results and Table 8 shows the hypotheses testing results.

Table 7a. Mediation Analysis (Total Effect)

Total Effect		
	Coefficient	**p-value**
Money Anxiety -> Investment Decisions	-0.299	0.000
Stress -> Investment Decisions	-0.295	0.000
Social Interaction -> Investment Decisions	-0.243	0.000
Internal Locus of Control -> Investment Decisions	-0.028	0.653

Table 7b. Mediation Analysis (Direct Effect)

Direct Effect		
	Coefficient	**p-value**
Money Anxiety -> Investment Decisions	-0.394	0.000
Stress -> Investment Decisions	-0.218	0.000
Social Interaction -> Investment Decisions	-0.133	0.003
Internal Locus of Control -> Investment Decisions	-0.260	0.000

Table 7c. Mediation Analysis (Indirect Effect)

	Indirect Effect				
	Coefficient	**SD**	**T value**	**P Values**	**BI [2.5%; 97.5%]**
H1: Money Anxiety -> Herding Bias -> Investment Decisions	0.095	0.027	3.563	0.000	0.044 - 0.149
H2: Stress -> Representativeness Bias -> Investment Decisions	-0.077	0.024	3.232	0.001	-0.128 - -0.033
H3: Social Interaction -> Overconfidence Bias -> Investment Decisions	-0.110	0.028	3.979	0.000	-0.174 - -0.067
H4: Internal Locus of Control -> Self-Serving Bias -> Investment Decisions	0.232	0.056	4.127	0.000	0.121 – 0.341

Table 8. Hypotheses Testing Results

Hypothesis	Result
Hypothesis 1 (H1): Money anxiety causes herding bias which, in turn, affects the investment decisions in cryptocurrencies negatively.	**H1 is supported**. The tables above reveal that the total effect of IV on DV was significant (β = -0.299, t = 6.407, p = 0.000). With the inclusion of mediating variable (MV), the impact of IV on DV is significant (β = -0.394, t = 11.972, p = 0.000). The indirect effect of IV on DV through MV was found significant (β = 0.095, t = 3.563, p = 0.000). **This shows that the relationship between IV and DV is partially mediated by MV**. However, the mediation is competitive since direct and indirect effects are pointing to opposite directions. Moreover, positive indirect effect is also in contradiction with the proposed hypothesis.
Hypothesis 2 (H2): Stress leads to representativeness bias which, in turn, undermines investment decisions in cryptocurrencies.	**H2 is supported**. The tables above reveal that the total effect of IV on DV was significant (β = -0.295, t = 4.062, p = 0.000). With the inclusion of mediating variable(MV), the impact of IV on DV is significant (β = -0.218, t = 3.545, p = 0.000). The indirect effect of IV on DV through MV was found significant (β = -0.077, t = 3.232, p = 0.001). **This shows that the relationship between IV and DV is partially mediated by MV**.

Hypothesis 3 (H3): Social interactions generate overconfidence bias which, in turn, affects the investment decisions negatively	**H3 is supported**. The tables above reveal that the total effect of IV on DV was significant (β = -0.243, t = 6.180, p = 0.000). With the inclusion of mediating variable (MV), the impact of IV on DV is significant (β = -0.133, t = 2.992, p = 0.003). The indirect effect of IV on DV through MV was found significant (β = -0.110, t = 3.979, p = 0.000). **This shows that the relationship between IV and DV is partially mediated by MV**
Hypothesis 4 (H4): Internal locus of control generates self-serving bias which, in turn, damages the quality of investment decisions.	**H4 is not supported**. The tables above reveal that the total effect of IV on DV was insignificant (β = -0.028, t = 0.449, p = 0.653). With the inclusion of mediating variable (MV), the impact of IV on DV is, however, significant (β = -0.260, t = 5.754, p = 0.000). The indirect effect of IV on DV through MV was found significant (β = 0.232, t = 4.127, p = 0.000). **This shows that the relationship between IV and DV is not mediated by MV** as per Baron & Kenny (1986) because of insignificant total effect.

Explanatory Power of the Model

The R^2 or coefficient of determination was used to determine the model's explanatory ability. R^2 was calculated using the PLS algorithm in Smart PLS, and all values, except herding and representativeness biases, were found to be greater than the proposed threshold of 0.10 as shown in Table 9. The Adjusted R^2 values are also reported in the table below which are deemed more appropriate since they penalize R^2 by the degree of freedom in the case of multiple independent variables. The Adjusted R^2 value for investment decisions in cryptocurrency, the main dependent variable, is 0.675 which indicates that 67.5% of variance in the dependent variable is explained by the independent variables in the model which represents an impressive goodness-of-fit (Falk and Miller 1992).

Table 9. *Coefficient of Determination Assessment*

Construct	R Squared	R Squared Adjusted
Investment Decisions (Dependent Variable)	0.683	0.675
Herding Bias (Mediator)	0.071	0.068
Overconfidence Bias (Mediator)	0.177	0.174
Representativeness Bias (Mediator)	0.092	0.089
Self-Serving Bias (Mediator)	0.592	0.591

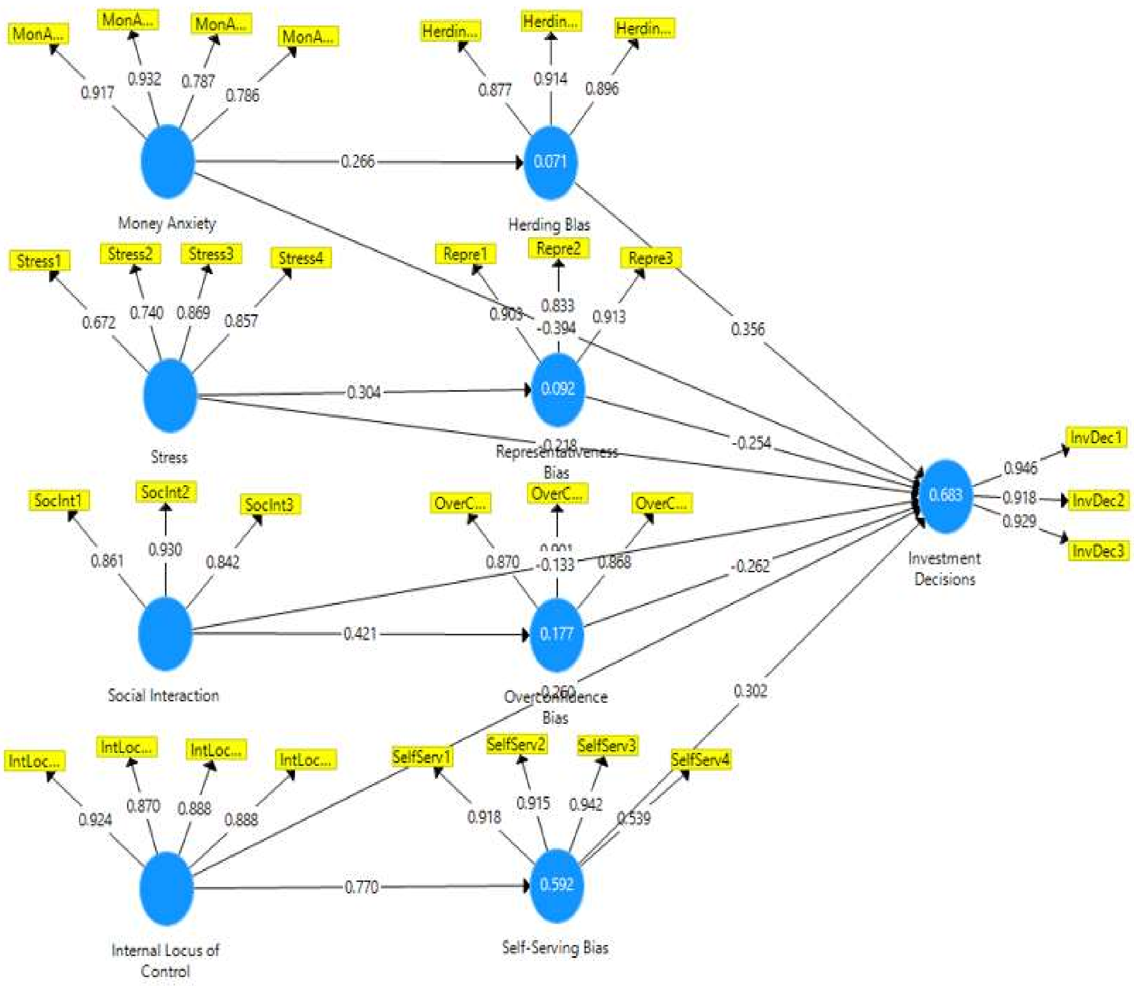
Predictive Relevance of the Model

We calculated cross validated redundancy (Q^2) to determine the model's predictive usefulness. The predictive usefulness of the model is determined, according to Hair et al. (2014), when all values of Q2 surpass zero. The results in Table 10 indicate that all Q2 values matched the specified criteria for determining the model's predictive significance.

Table 10. Q² Assessment

Construct	Q^2
Investment Decisions	0.585
Herding Bias	0.054
Overconfidence Bias	0.133
Representativeness Bias	0.046
Self-Serving Bias	0.415

Figure 2. Path Analysis Model (As Extracted from SmartPLS)



Conclusion

The goal of this research is to examine not just the effects of cognitive biases on investment decisions, but also the basic origins of these biases. By using partial least square structural equation modeling, we have derived the results that money anxiety, stress and social interactions are significant predictors of investors' decisions in cryptocurrencies via herding, representativeness and overconfidence biases. However, because of the insignificant total effect of internal locus of control on investment decisions, this study cannot establish a mediation effect of self-serving bias between internal locus of control and investment decisions. As hypothesized, this study concluded that high stress and social interactions in cryptocurrency investors damage the quality of their investment decision via representativeness and overconfidence bias. Whereas, as hypothesized, this research concluded that money anxiety affects investment decisions negatively but when herding bias acts as the mediator, the effect (indirect) of money anxiety turns out to be positive on investment decisions. The results of this study are to some extent consistent with Boussaidi (2013); Kim and Nofsinger (2007); Tan, Chiang, Mason and Nelling (2008). We examined financial decision-making theories in this study and found that stress, social interactions, and money anxiety indeed lead to cognitive biases such as representativeness bias, overconfidence bias, and herding bias which, in turn affect investment decisions in the context of crypto-investors in Pakistan. The findings of these results are further in sync with Hall, Ariss, and Todorov (2007).

Research Implication

The results derived from this study have potential implications including theoretical as well as practical. On the theoretical front, this study provides a strong empirical support for the theories in behavioral finance, such as prospect and heuristics theory, particularly, in the context of an ultra-risky investment, i.e. cryptocurrency which is pretty much an unexposed area in the existing literature. Moreover, there is a dearth of such studies in the literature on behavioral finance from emerging economies, such as, Pakistan. The theorized effects of cognitive biases on investment decisions is further validated through this research. Moreover, this study investigates the sources behind the popular cognitive biases which provides additional insights into the existing literature in this domain. On the practical side, this study can be helpful for cryptocurrency investors to understand the socio-psychological factors responsible for the generation of cognitive biases that lead to irrational decision making. Therefore, the investors will be able to analyze their decisions with the lens of their socio-psychological attributes and as a result they should be able to understand as to why they fall prey to cognitive biases and how they can overcome those underlying factors and make more informed, rational and unbiased decisions.

Recommendations

This study investigates whether cognitive biases play a vital role in predicting cryptocurrency investment performance in Pakistan. This research concludes that these biases are caused by a combination of socio-psychological factors and therefore have a significant impact on the performance of investment decisions of individual investors in cryptocurrencies. It is possible for investors to make a sensible judgement if psychological influences can be controlled. In a nutshell, this is an in-depth investigation into the underlying causes of cognitive biases, with a focus on their mediational function in investment decision-making in cryptocurrencies and the results indicate overall significant findings as hypothesized. Since investing into cryptocurrency is an extremely risky venture, investors ought to be extra cautious of their decision making. Particularly, they must take it account as to what social and psychological factors might affect their rash decision making so that they do not fall prey to the cognitive biases and make sound and rational decisions. At the market level, the governmental agencies should also step in this sector and raise awareness for crypto-investors so that they are cautious in their decisions and manage risk in an efficient manner

Research Limitations and Future Work

This study collected data mainly from the cities of Karachi and Hyderabad in Pakistan due to resource and time constraints, therefore, the results cannot be generalized to the entire country. Future similar studies, however, can be conducted in smaller cities where the cryptocurrency investors might have different dispositions due to different socio-economic factors. Although the sample size was statistically justified, it can be further increased in future researches as that might make the results more generalizable. Random sampling could not have been used in this study because of the scattered nature and inexact quantity of the population of this study. Risk aversion tendencies can also be taken as a moderator in the model in future researches and the effects could be examined on investment decisions in derivative securities in Pakistan Mercantile Exchange.

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