International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(6s) 2026 pp. 508-521
https://doi.org/10.70917/ijcisim-2026-2952
Article

# Understanding Cryptocurrency Investment Decisions Through Heuristic Biases and Investor Experience

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**Abstract:** Cryptocurrency markets are characterized by high volatility, limited valuation benchmarks, and rapid information flows, creating conditions under which investors are likely to rely on their mental shortcuts while making investment decisions. This study examines the influence of four heuristic biases viz. representativeness, overconfidence, anchoring, and gambler's fallacy on cryptocurrency investment decision-making. It also examines the moderating role of investment experience on the relationship between these heuristic biases and investment decision making. The study uses Partial Least Square Structural Equation Modelling (PLS–SEM) to examine the survey data from 604 individual investors investing in the cryptocurrency market in India. The findings indicate the significant influence of representativeness bias, anchoring bias, and gambler's fallacy bias on investment decision in cryptocurrency market. Whereas, overconfidence bias showed insignificant impact. The results of moderation analysis indicates that investment experience had no effect on the relationship between heuristic biases and investment decisions. It suggests that behavioral biases exist regardless of investing experience. The findings of the study provide valuable insights into the different behavioral biases of the cryptocurrency market investors. The study offers practical, academic as well as implications for regulators. This study exclusively relied on heuristic biases. This has been considered as the limitation of the study. In reality many other behavioral biases may influence investment decision.

**Keywords:** Heuristic biases, Representativeness bias, Overconfidence bias, Anchoring bias, Gambler's fallacy bias, Cryptocurrency investment

## 1. INTRODUCTION

The study of investment decision-making in financial markets has been a significant area of research over a period of time. Traditional finance theories such as the Efficient Market Hypothesis (Fama, 1970) and the Modern Portfolio Theory (Markowitz, 1952) assume that investors are rational, process all relevant information fully and correctly and act in their best interest maximizing expected utility. However, the behavioral finance studies indicates that investors do not act in line with traditional finance theories and they are influenced by psychological and behavioral biases (Shefrin, 2002; Lo, 2004). Bernstein (1995) stated that investors demonstrate inconsistency, irrationality and incompetence while taking investment decisions. Investors apply behavioral heuristics which help them to simplify the decision-making process under uncertainty. However, these heuristics cause a systematic deviation from rational behavior leading to permanent market anomalies and mispricing (Kahneman & Tversky, 1974; Piotrowski & Bünnings, 2024).

In the cryptocurrency markets which is characterize by high volatility, limited traded history and rapid information dissemination in the digital world, psychological factors are thought to play a very important and dominant role (Zhao & Zhang, 2021). This is due to the fact that cryptocurrency has no cash flow or a benchmark valuation formula. The value of the cryptocurrencies is often pegged to the investors' intuition and mental shortcuts. Empirical research in the recent times have explained the influence of behavioral factors like overconfidence, anchoring, representative bias and gambler's fallacy on the investment decisions of the investors in cryptocurrency markets (Song, 2025; Denura and Soekarno,2023).

Investors often use heuristics to make investment decisions based on simple mental shortcuts instead of probabilities. In the context of stock prices, investors are prone to biases such as the representativeness bias where investors base their judgments based on similarity to past experiences and situations instead of objective probabilities leading to a high degree of trend following and speculation (Shah et al., 2017). Overconfidence is also a dominant bias where investors feel they have superior knowledge over stock prices and subsequently engage in riskier investment decisions (Meier & De Mello, 2020). Anchoring bias leads an investor to make their decision on the basis of initial information they received such as purchase price at which they bought (Tversky & Khaneman, 1974). On the other hand, gambler's fallacy bias involves the mistaken belief that random price sequences will self-correct over time, prompting investors to anticipate reversals without statistical justification (Tversky & Kahneman, 1974).

Empirical studies over the years have already verified existence of behavioral biases in the traditional financial markets. However, there are limited studies which analyses the impact of behavioral biases in the cryptocurrency market. Due to the high volatility in the cryptocurrency market, the price movements are often affected by various behavioral biases (Al-Mansour, 2020). These biases can significantly affect investors' investment decisions, leading to suboptimal outcomes. This study investigates how behavioral biases specifically, heuristic biases (representative bias, overconfidence bias, anchoring and gambler's fallacy bias) affect the investors' decisions in cryptocurrency market. In this attempt it seeks answer the question: Do heuristic biases affect the investment decisions of individual investors investing in cryptocurrency market. Behavioral finance theory further argues that the impact of these biases is not uniform across the different investor classes rather it varies with individual characteristics, most notably the investment experience. Less experienced investors are more likely to rely on mental shortcuts in comparison to experienced investors who gradually develop greater awareness of market randomness through repeated exposure (Glaser & Weber, 2007; Waweru et al., 2008). Considering the relevance of investment experience, this study further investigates the moderating role investment experience on the relationship between heuristic biases and investment decision making.

Despite the growing interest in the behavioral aspect of cryptocurrency investment, most of the studies are focused in developed nations, leaving a gap in understanding the impact of behavioral factors in emerging nation like India. Also, previous research in this field treats various behavioral biases as independent variables but fails to categories the biases into established framework. Addressing these gaps, this study contributes to the existing literature of behavioral finance in cryptocurrency market. This study is based on the individual investors investing in cryptocurrency market in India, a developing nation that has not received as much attention previously as developed nations (Chen et al., 2022; García-Monleón et. al., 2023; Kumar and Rani, 2024). Another reason of conducting this study in India is that the developing economies faces the problem of financial literacy in comparison to the developed nations, which significantly impact the behavioral biases and investment decision of making process (Rasool and Ullah 2020). Also, this study fills gap in the existing literature on behavioral finance by categorizing the behavioral biases within the established framework of heuristic driven biases.

The structure of the study is divided in to several sections. The first sections contain the introduction to the research topic. Followed by the literature review with hypothesis formulation and conceptual framework in the second section. The third section is based upon the research methodology used in the study. Followed by the findings and implications of the study discussed in the fourth section. At last, in fifth section it contains the conclusion along with limitations of the study and future directions.

## 2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

### *2.1 Heuristic Biases and Investment Decision-Making in the Cryptocurrency Market*

Empirical studies over the years have provided strong evidence clamming the influence of behavioral factors on investment decision making. Originally Kahneman and Tversky's prospect theory (1979) laid down the framework of behavioral finance by showcasing that individuals' decisions are not strictly rational rather influenced by cognitive biases and heuristics. Heuristic can be defined as the mental shortcuts used by the individuals in a complex and uncertain environment. Initially, Tversky and Kahneman (1974) explained heuristic by incorporating three behavioral biases: availability, representativeness, and anchoring. Waweru et al. (2008) extended the scope of heuristics by including two more biases: gamblers' fallacy and overconfidence (Jain et al., 2020). While making investment decisions, investors are prone to mental shortcuts and take irrational decisions rather than taking decisions based on the relevant information (Kahneman and Tversky 1979). Heuristics is often used by the investors in decision making, due to the limitation of the time and in uncertain and complex environment. But using these mental shortcuts often results into systematic errors leading to poor investment decisions (Waweru et al., 2008).

Empirical studies in the traditional financial markets have consistently shown the impact of heuristic biases in shaping investors behavior, resulting in to deviations from optimal decision-making (Barber & Odean, 2001). The cryptocurrency market due to its inherent characteristics like, high volatility, limited historical depth, and speculative trading makes it an ideal setting for heuristic driven behavior. Cryptocurrency investors are often driven by mental shortcuts like intuition, recent price movements, and subjective beliefs, strengthening the role of heuristic in decision making (Corbet et al., 2019). Empirical studies in the field of cryptocurrency recognize heuristic biases as among the most influential psychological determinants of cryptocurrency investment behavior (Gunasena et al., 2025; Mulyadi et al., 2025). Based upon this background, this study incorporates four core heuristic biases (representativeness, overconfidence, anchoring, and gambler's fallacy) to examine their influence on investment decisions in cryptocurrency markets.

### *2.2 Representativeness bias and investment decisions cryptocurrency market*

Representative bias also known as familiarity bias is a heuristic bias where investors take decisions based on recent or small samples rather than objective data. When the full information is not available, neural connections in the brain uses shortcuts for processing information and the information processing is done based on the recent experience (Busenitz and Barney 1997). Due to representativeness, individuals give more importance to recent experience and ignore the average long-term rate (Ritter, 2003). Shefrin (2010), explains representative bias as a mental shortcut used to take decisions based on mental stereotypes.

Empirical studies across equity market have shown the positive influence of representativeness on investment decisions. Toma (2015) while investigating the impact of behavioral biases on investment decision in Romanian stock market, found the positive influence of representativeness bias on investment decisions. Irshad et al. (2016) and Ikram (2016) also found the positive relationship between representative bias on investment decisions, suggesting that the returns generated by the investors, increased sue to representativeness bias. As far as cryptocurrency market is concerned, the impact of representativeness bias can be more evident due to the characteristics of the market like extreme and media driven price movements. Recent empirical studies on cryptocurrency markets have reported that the investors in this market more often make their decisions based on historical highs or recent price surges, interpreting these signals as predictors of future returns, despite weak fundamentals. Accordingly, representativeness bias is expected to have a positive significant influence on cryptocurrency investment decisions.

**H1:** Representativeness bias significantly influences investment decisions in cryptocurrency markets.

### *2.3 Overconfidence bias and investment decisions in cryptocurrency market*

Overconfidence bias is a heuristic bias, which can be defined as unwarranted faith in one's intuitive reasoning, judgments, and cognitive abilities (Pompain, 2011). It reflects the tendency of investors to overestimate their knowledge, skills, and control over investments returns (Barber & Odean, 2001). Moore and Healy (2008), explains three attributes of overconfidence bias: Over estimation, over-placement and over-precision.

Empirical studies across the financial markets have shown the significant impact of overconfidence bias on investment decisions. Bakar and Yi (2016) in a study found that overconfidence bias has a positive influence on investors' decision making. Investors suffering from overconfidence bias, trade more frequently and underestimate risk while making investment decisions (Glaser & Weber, 2007). Baker and Nofsinger (2002), found that investors prone to overconfidence bias, underestimate risk factors and overestimate projected profit.

In context to cryptocurrency markets, overconfidence bias can influence decision making due to attributes of cryptocurrency markets like low entry barriers, widespread social media narratives, and anecdotal success stories. Previous studies in this context have shown overconfidence as a major behavioral factor influencing cryptocurrency investment decisions. In a study Handoko et al. (2024) found that cryptocurrency investors are overconfident as they believe they can believe that they can outperform the market through knowledge, strategies, and technical skills. On this basis, overconfidence bias is expected to influence cryptocurrency investment decisions.

**H2:** Overconfidence bias significantly influences investment decisions in cryptocurrency markets.

## *2.4 Anchoring bias and investment decisions in cryptocurrency market*

Anchoring bias also known as adjustment bias is a heuristic bias, which explain individuals' tendency to rely on initial piece of information often called as "the anchor" like news, trade volume, one day returns while making investment decisions (Andersen, 2010). Anchoring bias occurs when an investor uses a first piece of information to make investment decision. Once the anchor is set, then all other judgments revolve around it (Pompain, 2011). Some common anchors include historical highs, purchase price, and salient round numbers (Waweru et al., 2008).

Results from prior studies shows that anchoring bias influences portfolio evaluation, purchase and selling behavior, and risk assessment (George & Hwang, 2004). Anchoring bias is a found to be major heuristic bias, positively influencing the investment decision making across equity markets (Waweru et al., 2008; Ishfaq & Anjum, 2015; Luong & Ha, 2011).

In cryptocurrency investment decisions, anchoring bias holds a prominent position due to the continuous visibility of price histories and frequent emphasis on all-time highs. Recent studies in this context have also verified the influence of anchoring bias. Found that investors often hold losing cryptocurrency in a hope of a return to anchored price level or they delay selling profitable cryptocurrency due to fixation on a higher reference price (Mulyadi, 2025). Accordingly, anchoring bias is expected to significantly influence cryptocurrency investment decisions.

**H3:** Anchoring bias significantly influences investment decisions in cryptocurrency markets.

## *2.5 Gambler's fallacy bias and investment decisions in cryptocurrency market*

Gambler's fallacy bias is described as the act of estimating the likelihood of an outcome based on its probability over repeated trials. It is also known as the 'Monte Carlo Fallacy' (Chen et al., 2022). This is caused due to inappropriate prediction made by the investors and such anticipation may be good or poor (Waweru et al., 2008). The stock market investors are driven by the gambler's fallacy which refers to the misguided belief of an investor that a repeated event in the past is less likely to reoccur in the future and vice versa (Kahneman & Tversky, 1974).

Although, gambler's fallacy bias is academically a less examined in comparison to other heuristic biases, existing studies suggest to have a positive influence of gambler's fallacy on investment decisions (Jain et al., 2023). In context to cryptocurrency market, high volatility often triggers premature entry or exist decisions based on the mistaken belief that prices will immediately revert to the average (Kumar et al., 2024). Recent studies in the cryptocurrency market indicates that gambler's fallacy contributes to mental shortcuts among crypto investors. Therefore, gambler's fallacy is expected to influence cryptocurrency investment decisions.

**H4:** Gambler's fallacy bias significantly influences investment decisions in cryptocurrency markets.

## *2.6 Investment Experience as a Moderating Variable*

Behavioral finance studies consistently highlight the relevance of investment experience as a key factor shaping investors' reliance on behavioral biases. Investors having less investment experience face more cognitive constraints and depend heavily on mental shortcuts or heuristic biases while making investment decisions under uncertainty (Waweru et al., 2008). On the other hand, experience in financial markets facilitates more feedback learning, enabling investors to recognize patterns of error and adopt more analytical decision making (Glaser & Weber, 2007).

In cryptocurrency market which is relatively new and the investors lack long-term exposure and formal investment training, investment experience is anticipated to play a vital moderating role in the relationship between behavioral biases and investment decision making. Based on which the following hypothesis are framed:

**H5:** Investment experience moderates the relationship between heuristic biases and cryptocurrency investment decision-making.

**H5a:** Investment experience moderates the relationship between representativeness bias and cryptocurrency investment decision-making.

**H5b:** Investment experience moderates the relationship between overconfidence bias and cryptocurrency investment decision-making.

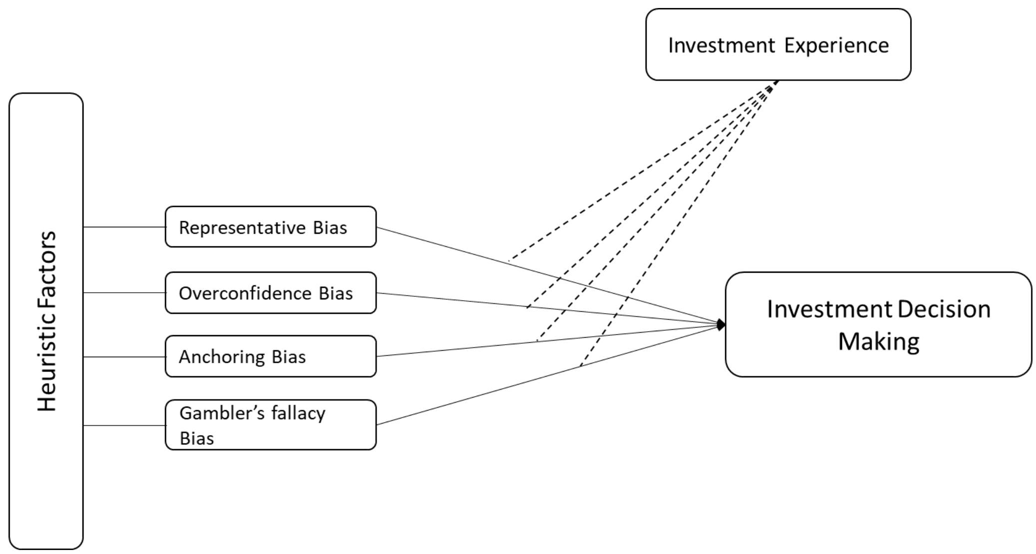
**H5c:** Investment experience moderates the relationship between anchoring bias and cryptocurrency investment decision-making.

**H5d:** Investment experience moderates the relationship between gambler's fallacy bias and cryptocurrency investment decision-making.

## *2.7 Research model*

Based on the extensive literature review, this study explores the influence of four heuristic biases representativeness, overconfidence, anchoring, and gambler's fallacy on investment decision making in cryptocurrency market in India. Also, it studies the moderating impact of investment experience on the relationship between these heuristic biases and investment decision making. **Figure 1.** Illustrates the theoretical framework of the study.

**Figure 1: Proposed conceptual model on heuristic biases and investment decision making**




**Source(s):** Authors' own work

# 3. RESEARCH METHODOLOGY

The study employed a cross-sectional survey-based descriptive research design. The theoretical foundation of the study is shown in **Figure 1**. The dependent variables in the study are the heuristic biases (representativeness, overconfidence, anchoring, and gambler's fallacy) and the dependent variable is investment decision making. Whereas, the investment experience serves as the moderating variable.

## *3.1 Questionnaire Design*

In order to test the cause-and-effect relationship between heuristic biases and investment decision making in the cryptocurrency market, a modified structured questionnaire has been used for data collection. The questionnaire consists 20 items adopted from the existing literature on behavioral biases. In order to confirm whether the measurement items are properly worded and understandable, the face validity of the measurement scale was analyzed. Initially the questionnaire was submitted with 11 experts, based on their recommendations several changes were made. Further pilot testing was conducted and for the purpose questionnaire was sent to 55 cryptocurrency investors for their responses. The final questionnaire consisted of two sections and the responses to the items was recorded on 5-Poin Liker scale. The first section contains questions pertaining to demographic information. Whereas the second section contains questions pertaining to heuristic biases and investment decision making.

## *3.3 Sampling process and Data Collection*

The target population of the study includes individual investors from India investing in the cryptocurrency market. This study employed a nationwide approach as it collected the data from the respondents throughout several regions of India. This nationwide approach guarantees a thorough and representative understanding of investment behavior (Stuart et al., 2015).

Snowball sampling technique was applied to collect the data from the respondents. It was considered as the appropriate technique in this case as the previous studies had established that snowball sampling is a most suited techniques in a scenario where there is a difficulty in the accessibility of population (Wagner & Lee 2014). The data was collected in between September 2025 and February 2026 using an online questionnaire administered through Google forms. The questionnaire was distributed amongst the respondents through email, WhatsApp, social media groups, and through cryptocurrency exchange communities. A total of 630 replies were obtained out of which 26 were omitted as they were considered outliers using the standard deviation technique. Subsequently, 630 responses were taken for final data analysis.

## 4. DATA ANALYSIS

This study aims to predict the investment decision making behavior of the investors in cryptocurrency market by analyzing the casual relationship between the variables. The PLS-SEM approach is used to measure the casual relationships between the variables applied more often recently (Hair et al., 2017). In this study, the data is analyzed using Smart PLS 4.1.0.9 software.

### *4.1 Demographic characteristics*

**Table 1.** shows the sample's demographic characteristics. The results illustrate that 395 out of 604 (66.40%) are males whereas 209 out of 604 (34.60%) are females, the majority of respondents turned out to be male. The results show that 375 of the 604 people who answered (62.08%) are between the ages of 21 and 30, which means that this group is the largest in the population. There were 95 people (15.72%) in the 31–40 age group and 83 people (13.74%) in the under-20 age group. Furthermore, most respondents, 272 (45.03%), hold a Bachelor's Degree, while 230 (38.07%) have obtained a Master's Degree, indicating that a significant portion of the population has participated in higher education. A small number, 69 (11.42%), only have a high school diploma, while 33 (5.46%) have a Ph.D. or higher, which shows that they are very well-educated. The data shows that 88.56% of the people who answered have at least a bachelor's degree.

The largest group, with 245 people (40.56%), said they had 1–2 years of experience. This means that many investors are still new to the cryptocurrency market but have moved on from the first entry phase. After that, 190 respondents (31.45%) have less than a year of experience, which means that a lot of the people who took part are new to this growing investment field. A small group of 148 respondents (24.50%) have 2 to 5 years of experience, which shows that they know a moderate amount about the market. In the end, only 21 respondents (3.47%) said they had more than 5 years of experience, showing that experienced investors with a lot of knowledge are a small group.

**TABLE 1. DEMOGRAPHIC CHARACTERISTICS**

| **Characteristics** | **Frequency** | **Percentage** |
|---|---|---|
| **Gender** | | |
| Male | 395 | 66.4% |
| Female | 209 | 34.6% |
| **Age** | | |
| Less than 20 years (1) | 83 | 13.74% |
| In between 21-30 years (2) | 375 | 62.08% |
| In between 31-40 years (3) | 95 | 15.72% |
| More than 40 years (4) | 51 | 8.44% |
| **Educational Qualification** | | |
| High school (1) | 69 | 11.42% |

| | | |
|---|---|---|
| Bachelor's Degree (2) | 272 | 45.03% |
| Master's Degree (3) | 230 | 38.07% |
| Ph.D. or Higher (4) | 33 | 5.46% |
| **Experience of investing in Cryptocurrencies** | | |
| Less than 1 year (1) | 190 | 31.45% |
| In between 1-2 Years (2) | 245 | 40.56% |
| In between 2-5 years (3) | 148 | 24.50% |
| More than 5 Years (4) | 21 | 3.47% |

**Source(s):** Authors' own work

### *4.2 Analysis of measurement model*

The first part of data analysis using PLS-SEM approach was to analyze the measurement model to evaluate the reliability and validity of the model. The first step in the measurement model was to check indicator loadings, convergent validity and composite reliability (Hair et al., 2019). Indicator loadings were evaluated by measuring the outer loadings, while composite reliability was analyzed using Cronbach's alpha and composite reliability (rho_a). Convergent validity was established through the Average Variance Extracted (AVE) (Hair et al., 2019, 2022). In the next step of measurment model was to analyse the discriminant validity using the heterotrait–monotrait (HTMT) ratio (Hair et al., 2019, 2022). The results of these anlysis indicate that the measurment model exhibits satisfactory realiabilty and validity.

As reported in Table 2. all the cosntructs demonstartes strong reliability and vaidity. The factor loadings for all the items are above the thresehold limit of 0.7. The values of Cronbach's alpha and composite reliability (rho_a) are above the threshold limit of 0.70, indicating strong realiability. The AVE values for all constructs are qbove the minumum criterion of 0.50, indicating the strong convergent validity of the model.

**TABLE 2. CONSTRUCT RELIABILITY AND VALIDITY STATISTICS**

| Construct | Items | Outer Loadings | Cronbach's alpha | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|---|
| **Representativeness bias** | RTB1 | 0.751 | 0.754 | 0.844 | 0.575 |
| | RTB2 | 0.736 | | | |
| | RTB3 | 0.778 | | | |
| | RTB4 | 0.767 | | | |
| **Overconfidence Bias** | OB1 | 0.801 | 0.825 | 0.882 | 0.651 |
| | OB2 | 0.852 | | | |
| | OB3 | 0.839 | | | |
| | OB4 | 0.731 | | | |
| **Anchoring bias** | AN1 | 0.716 | 0.709 | 0.821 | 0.534 |
| | AN2 | 0.775 | | | |
| | AN3 | 0.700 | | | |
| | AN4 | 0.729 | | | |
| **Gambler's fallacy bias** | GF1 | 0.861 | 0.754 | 0.853 | 0.660 |
| | GF2 | 0.815 | | | |
| | GF3 | 0.758 | | | |
| **Investment Decision Making** | IDM1 | 0.784 | 0.822 | 0.875 | 0.584 |
| | IDM2 | 0.818 | | | |

| | |
|---|---|
| IDM3 | 0.728 |
| IDM4 | 0.769 |
| IDM5 | 0.719 |

**Source(s):** Authors' own work

Further, discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio (Henseler et al., 2015; Hair et al., 2020). Previous studies support the use of the HTMT criterion as a more rigorous and reliable approach than cross loadings (Henseler et al., 2014; Hair et al., 2019). As reported in Table 3, all HTMT values are below the recommended threshold of 0.90, indicating adequate discriminant validity across all constructs (Hair et al., 2019). This indicates that the constructs in the model are empirically distinct from each other.

**TABLE 3. HETEROTRAIT-MONOTRAIT RATIO (HTMT) FOR DISCRIMINANT VALIDITY ASSESSMENT**

| | AN | GF | IDM | OB | RTB |
|---|---|---|---|---|---|
| **AN** | | | | | |
| **GF** | 0.559 | | | | |
| **IDM** | 0.774 | 0.405 | | | |
| **OB** | 0.482 | 0.356 | 0.393 | | |
| **RTB** | 0.640 | 0.259 | 0.563 | 0.409 | |

**Source(s):** Authors' own work

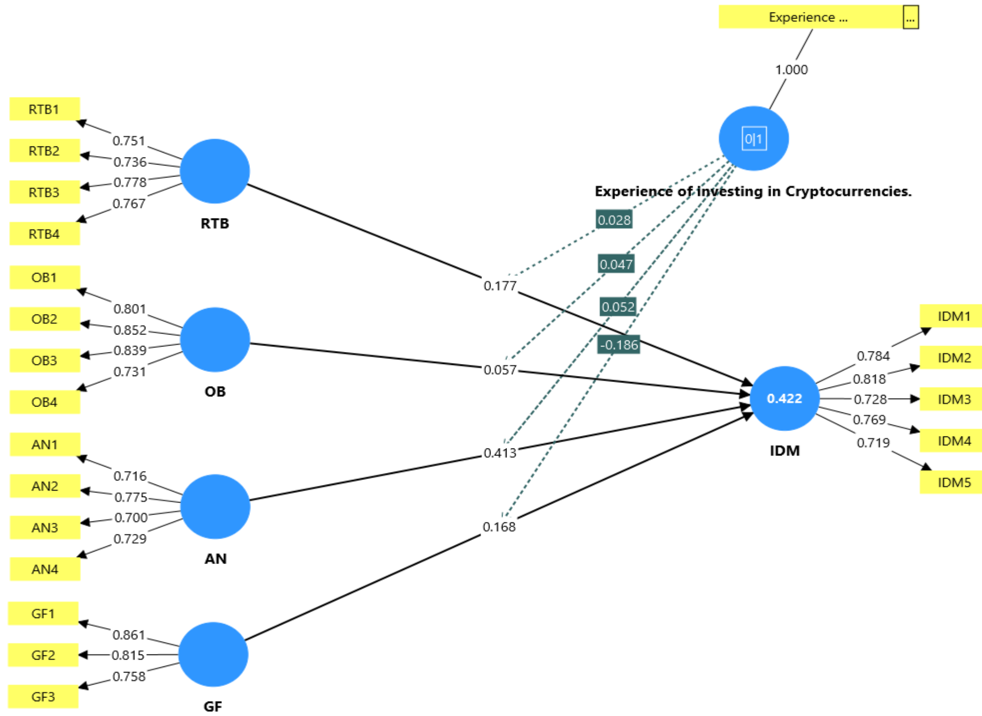
### *4.3. Analysis of Structural Model*

The second part of data analysis using PLS-SEM approach was to analyze the structural model. The structural model was evaluated following the guidelines of Hair et al. (2017) and Hair et al. (2019). **Figure 2** Illustrates the structural model relationship. In the first step of structural model assessment, collinearity was analyzed using the variance inflation factor (VIF) values. All VIF values were below the conservative threshold of 3, indicating that there was no collinearity issue existed in the model (Kock, 2015).

In the next step the hypotheses were tested using bootstrap technique with a subsample of 10,0000 as recommended by Hair et al. (2022). The result showed that, representativeness bias has a positive and statistically significant influence on investment decision making in the cryptocurrency market ($\beta = 0.178$, $t = 2.718$, $p = 0.003$), resulting in the acceptance of hypothesis H1. Overconfidence bias did not have a significant impact on the investment decision making in cryptocurrency market ($\beta = 0.061$, $t = 0.908$, $p = 0.182$). Hence, hypothesis H2 was not supported.

Anchoring bias ($\beta = 0.414$, $t = 6.938$, $p < 0.001$) as well as the gambler's fallacy ($\beta = 0.168$, $t = 2.731$, $p = 0.003$) bias were found to have a positive and significant influence on the investment decision making in cryptocurrency market. Therefore, supporting hypotheses H3 and H4. Beyond heuristic biases, investment experience ($\beta = 0.181$, $t = 1.947$, $p = 0.026$) also found to have a significant direct impact on investment decision making. The results of the hypotheses testing for each relationship are summarized in **Table 4.**

**FIGURE 2: STRUCTURAL MODEL**




**Source(s):** Authors' own work

**TABLE 4. ASSESSMENT OF HYPOTHESES**

| Hypothesis | Variables relationships | Beta | STDEV | T statistics | P Values | Decision |
|---|---|---|---|---|---|---|
| **H1** | Representativeness bias -> Investment decision making | 0.178 | 0.065 | 2.718 | 0.003 | Supported |
| **H2** | Overconfidence Bias -> Investment decision making | 0.061 | 0.063 | 0.908 | 0.182 | Not Supported |
| **H3** | Anchoring bias -> Investment decision making | 0.414 | 0.059 | 6.938 | 0.000 | Supported |
| **H4** | Gambler's fallacy bias -> Investment decision making | 0.168 | 0.061 | 2.731 | 0.003 | Supported |
| | Investment Experience -> Investment decision making | 0.181 | 0.096 | 1.947 | 0.026 | Supported |

**Source(s):** Authors' own work

### 4.3.1 Moderation Analysis

The moderating role of investment experience in the relationship between heuristic biases and investment decision was assessed through interaction terms used in the structural model. The results represented in the **Table 5** showed that the moderating effect of the investment experience on the relationship between representativeness bias and investment decision making was insignificant (β = 0.039, t = 0.188, p = 0.425). Similarly, that the moderating effect of the investment experience on the relationship between overconfidence bias and investment decision making (β = 0.034, t = 0.395, p = 0.346) and on the relationship between anchoring bias and investment decision making (β =

0.051, t = 0.460, p = 0.323) were found to be statistically insignificant. Following these outcomes, H5a, H5b and H5c were not supported.

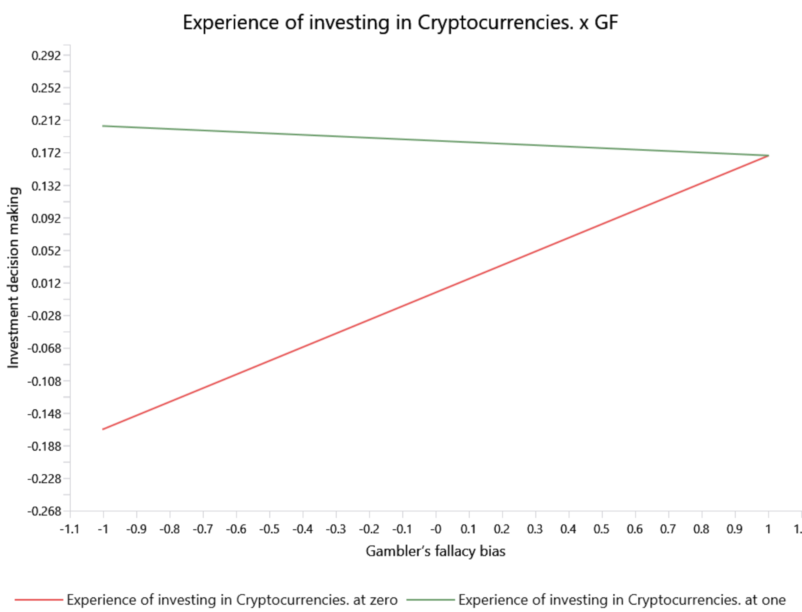
However, the moderating effect of the investment experience on the relationship gambler's fallacy bias and investment decision making was found to have a negative but significant effect ($\beta = -0.181$, t = 2.180, p = 0.015), thereby supporting H5d. The simple slope analysis illustrated in **Figure 3** provides further insights in to this moderating effect. It showed that the investors with less than two years of experience (experience = 0) shows a strong positive relationship between gambler's fallacy bias and investment decision making. Whereas for the investors with more than two years of experience (experience = 1), the slope was relatively flatter which indicated substantially weaker influence of gambler's fallacy bias an investment decision making.

**TABLE 5. ASSESSMENT OF MODERATION EFFECT**

| Hypothesis | Variables relationships | Beta | STDEV | T statistics | P Values | Decision |
|---|---|---|---|---|---|---|
| **H5a** | Experience of investing x Representativeness bias -> Investment decision making | 0.039 | 0.150 | 0.188 | 0.425 | Not Supported |
| **H5b** | Experience of investing x Overconfidence Bias -> Investment decision making | 0.034 | 0.120 | 0.395 | 0.346 | Not Supported |
| **H5c** | Experience of investing x Anchoring bias -> Investment decision making | 0.051 | 0.112 | 0.460 | 0.323 | Not Supported |
| **H5d** | Experience of investing x Gambler's fallacy bias -> Investment decision making | -0.181 | 0.085 | 2.180 | 0.015 | Supported |

**Source(s):** Authors' own work

**FIGURE 3: SLOPE ANALYSIS**



**Source(s):** Authors' own work

### *4.4 Model Accuracy:*

In the last step of the analysis, the overall accuracy and robustness of the model were evaluated using measure of explanatory power, effect size and predictive relevance. The results of the coefficient of determination showed that the model explains 42.2% of the variance in the investment decision making with R2 value 0.422. whereas, adjusted R2 value of 0.408 confirms moderate explanatory power (Hair et al., 2019). These results are in line with the previous studies in the field of behavioral finance. Further, **Table 6** demonstrates the model out of sample predictive power calculated using PLS-predict. The results showed that all indicators of investment decision making produced positive Q2 predict values, confirming predictive relevance.

**TABLE 6. PLS PREDICT RESULTS**

| Construct | Predictors | $Q^2$predict | PLS-SEM_RMSE | LM_RMSE | PLS-LM | Predictive Relevance |
|---|---|---|---|---|---|---|
| Investment decision making | **IDM1** | 0.253 | 0.840 | 0.840 | 0.000 | Moderate predictive power |
| | **IDM2** | 0.267 | 0.796 | 0.793 | 0.003 | |
| | **IDM3** | 0.170 | 0.841 | 0.852 | -0.001 | |
| | **IDM4** | 0.218 | 0.885 | 0.897 | -0.012 | |
| | **IDM5** | 0.144 | 0.940 | 0.953 | -0.013 | |

**Source(s):** Authors' own work

## 5. DISCUSSION AND IMPLICATIONS

The study started with a brief review of past literature on behavioral biases in particular heuristic biases. Based on the behavioral finance theory and heuristic processing theory, this study offered empirical insights on how these behavioral biases influence investment decision making in cryptocurrency market. Based on the literature review, heuristic biases were classified into representativeness bias, anchoring bias, overconfidence bias, and gambler's fallacy bias (Jain et al., 2023). Accordingly, a theoretical model was developed and assessed for validity and reliability. Further the results of the study offered conclusion on the influence of these biases on investment decision making in cryptocurrency market.

The results indicated that representativeness bias, anchoring bias and gambler's fallacy bias significantly influenced the investment decisions of cryptocurrency investors. These results were in line with the recent studies conducted by (Jain et al., 2023; Handoko et al., 2024) who in their studies proved the significant influence of heuristic biases on investors decision in cryptocurrency market which often led investors to rely on mental shortcuts than rational thinking while making investment decision in such uncertain market. The results pertaining to representativeness bias reflected that the investors tend to rely on perceived similarities between past and current price movements when making expectations about future cryptocurrency preferences. Similarly, the strong influence of anchoring bias reflects the investors' tendency to anchor their investment decision based upon important reference points such as initial purchase prices and historical highs of the assets. These results strengthen the previous findings that states anchoring bias remains prominent even in technological advanced environments like cryptocurrency market (Gautam & Kumar, 2023). Further the significant impact of gambler's fallacy bias supports the recent studies (Jain et al., 2023; Gautam & Kumar, 2023) suggesting that in highly volatile market like cryptocurrency, the investors frequently misinterpret the random events and expect for price reversal based on the past streaks of gains or losses. In contrast to the above discussed heuristic biases, overconfidence bias showed insignificant impact on investment decision making in cryptocurrency market. These results are in line with the recent studies in the cryptocurrency market (Yachna & Walia 2025). In traditional markets, overconfidence bias leads investors to overestimate their knowledge and skills which results in excessive trading and risk taking (Statman et al., 2006). However, in cryptocurrency market, the impact of overconfidence bias becomes relatively insignificant due to the structure of cryptocurrency market marked by extreme volatility, lack of regulations and speculative sentiment. Also, the investment experience showed positive and significant impact investment decision making suggesting that more experienced investors tend to show greater decisiveness in their investment choices in cryptocurrency market.

The results of the moderation analysis showed insignificant moderating impact of investment experience on the relationship between heuristic biases (representativeness bias, anchoring bias, overconfidence bias) and investment decision making in cryptocurrency market. These findings are in line with (Gautam & Kumar 2023**;** Chalissery et al., 2023). In contrast, investment experience has shown significant moderating impact on the relationship between gambler's fallacy bias and investment decision making. These findings are consistent with learning theory, which states that experience helps people understand probability and randomness better, but does not erase deeply rooted mental shortcuts like relying heavily on reference points. Recent studies also suggest that some biases can be corrected through experience while other still persist (Chalissery et al., 2023).

The findings of the study have practical, academic as well as regulatory implications. From practical point of view, investor education should go beyond basic financial knowledge and stress upon the impact of behavioral biases on investment decisions. Training modules could include exercise that demonstrates how these biases lead to pattern recognitions. The study also strengthens theoretical understanding in behavioral finance and investment psychology by contextualizing investor behavior within cryptocurrency market. As far as regulatory implications are concerned, regulators can also use these insights to strengthen investor protection while allowing innovation in cryptocurrency market. Overall, this study contributes to the behavioral finance literature by showcasing how heuristic biases operates differently across financial markets. Also, by isolating individual heuristics and examining their influence, the study offers a more refined understanding of investor behavior in cryptocurrency market.

## 6. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

The overall objective of this study was to analyze the impact of behavioral biases on invest decision in crypto currency market. Based on the prior literature, heuristic biases (representativeness bias, anchoring bias, overconfidence bias and gambler's fallacy bias) were taken into consideration. Accordingly, a conceptual model was developed and assessed in two stages, measurement model and structural model assessment.

The results of the study revealed that investors rely unevenly on heuristic biases in cryptocurrency market. Representativeness bias, anchoring bias, and gambler's fallacy bias significantly influence decision making. Whereas, overconfidence bias does not influence decision making in cryptocurrency market. Also, investment experience selectively moderates the influence of gambler's fallacy bias on investment decision in cryptocurrency market. It explains that repeated exposure to the market improves understanding of randomness. Overall, these results suggest that cryptocurrency environment tends to amplify certain behavioral biases while constraining others. Thes results gives us a more detailed picture of how investors psychology works in cryptocurrency environment.

Despite the contributions, this study is also subject to certain limitations. First, the dependence on self-reported survey data may introduces the possibility of response bias and limit the ability to capture actual investment behavior. Secondly, the sample is limited to retail cryptocurrency investors in India. Which may limit the generalizability of the findings. Finally, this study only focuses on selective behavioral biases (heuristic biases) and does not take in to consideration other behavioral biases such as prospect biases and herding biases. Future studies shall address these limitations by employing longitudinal or experimental design. Future studies shall collect data across the diverse cryptocurrency market segments. Also, future studies may take in to consideration other behavioral bias to analyze their impact on investment decision making in cryptocurrency market.

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