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"All are investing in Crypto, I fear of being missed out": examining the influence of herding, loss aversion, and overconfidence in the cryptocurrency market with the mediating effect of FOMO

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Abstract
The study's purpose is to examine the effect of herding, loss aversion, overconfidence, and fear of missing out (FOMO) biases on crypto investors' investment decisions. The study also looks at how FOMO plays a mediating role between herding, loss aversion, overconfidence, and crypto investment decisions. To acquire data from crypto retail investors, the study used a questionnaire survey. A total of 473 responses were gathered and analyzed with SmartPLS. To achieve the study's aims, factor analysis and partial least square structural equation modelling were used. The study's findings found that FOMO, herding, loss aversion, and overconfidence biases have a substantial effect on the investment decisions of crypto investors, in respective order. In addition, FOMO bias establishes a complementary partial mediation on the relationship between herding, loss aversion, and crypto investors' decision-making behavior. Ergo, the present study assisted individual and institutional cryptocurrency investors, crypto portfolio managers, policymakers, researchers, and market regulators in broadening their knowledge base about cryptocurrency and forecasting investors' behavior. Hence, this study contributes to the field of behavioral finance.

Keywords Herding · Loss aversion · Overconfidence · Fear of missing out (FOMO) · Crypto investment decisions

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1 Introduction

The unprecedented expansion of investment alternatives in the financial market has hitherto empowered the global economy on a large scale. Moving from simple stock or bond investments in the early 1900s to more complex financial derivatives instruments developed later in the decades, such as securities options, credit default swaps, futures, collateralized debt obligations, and so on, has incentivized investors with higher investment yields while introducing greater risk. This expansion has been spurred further due to the emergence of blockchain-based cryptocurrency (also known as crypto assets), which has garnered a lot of attention in the academic world as well as the business community owing to its rise over the last decade (Zhang and Zhang 2022). Its market's valuation increased at an astounding rate from USD 1.2 billion in 2013 to USD 2.16 trillion at the end of the financial year 2021–2022 (CoinMarketCap 2022). Primitively, the voyage of cryptocurrency started when Satoshi Nakamoto (an anonymous name) invented the first permissionless decentralized currency, Bitcoin, in 2009. The first commercial transaction using Bitcoin took place on May 22, 2010, when Laszlo Hanyecz paid 10,000 bitcoins (about $25) for two pizzas (Hidajat 2019; Arias-Oliva et al. 2019). However, it gained public prominence in 2011 when Julian Assange, the founder of Wikileaks, decided to accept donations in Bitcoin (Porterfield 2012). Subsequently, other crypto-tokens and altcoins such as Namecoin, Litecoin, Ripple, Dogecoin, and so forth have aggressively propelled themselves into the public eye (Sun et al. 2021). Numerous recent studies (e.g., Savelyev 2018; Abubakar et al. 2019; Mikhaylov 2020; Mosteanu and Faccia 2020; Delfabbro et al. 2021) have demonstrated that cryptocurrencies have cemented their place in today's digital world and will undoubtedly play a significant role in practically every investor's portfolio in the years to come.

However, cryptocurrency is a more volatile investment vehicle (Sun et al. 2021) compared to conventional asset classes of the stock market like commodities, stocks, and bonds (Subramaniam and Chakraborty 2020), and it is not backed by any government or commodity (Sood and Singh 2022). Corollary, the fundamental analysis of cryptocurrency investments for return predictability fails (Rubbaniy et al. 2022), whilst non-fundamental approaches such as herding (Gurdgiev and Corbet 2018; Bouri et al. 2019; Kaiser and Stöckl 2020; Vidal-Tomás et al. 2019; Yarovaya et al. 2021), loss aversion (Popova 2019; Haryanto et al. 2020), and overconfidence (Sudzina et al. 2021; Kim and Hanna 2021; Jalal and Leonelli 2021; Nurbarani and Soepriyanto 2022) emerged as the most prevalent drivers in the cryptocurrency market, which makes it more challenging to go through tough periods of downturns and dips. Despite this, the cryptocurrency market is seeing positive momentum day by day. The worldwide crypto market capitalization has surpassed $1.20 trillion, owing to high and consistent trade volumes (Maheshwari 2023). This growing rate of the cryptocurrency market is prompting many new investors to invest in cryptocurrency, which makes many investors apprehensive that they will lose a good return by not investing in it (Sood et al. 2023a, b). As a result, researchers have observed that the "fear of missing out" (FOMO) approach also has a substantial influence on crypto investors' investment decisions, along with other biases (e.g., Gupta and Shrivastava 2021). Notwithstanding the significant influence of FOMO on cryptocurrency investors' investment decisions, researchers have failed to examine empirically how various biases in the presence of FOMO affect investors' decisions to invest more in cryptocurrency.

Accordingly, this is the first study that, to the best of the researchers' knowledge, that has examined how FOMO affects the herding, loss aversion, overconfidence, and overall decision-making of crypto retail investors with the help of the following research questions (RQs): first, do herding, loss aversion, overconfidence, and FOMO biases have a significant impact on crypto retail investors' decision-making? Second, does FOMO play a mediating role between herding, loss aversion, and overconfidence biases and crypto investors' decision-making behavior? Ergo, the purpose of this study is to better understand how herding, loss aversion, overconfidence, and FOMO affect cryptocurrency investment decisions. It also attempts to provide a clear picture of whether FOMO mediates these relationships and, if so, whether it does so partially or fully. Thus, the present study assisted individual and institutional cryptocurrency investors, crypto portfolio managers, policymakers, researchers, and market regulators in broadening their knowledge base about cryptocurrency and forecasting investors' behavior. This study also helps the Indian government to make strong policy announcements that allow the cryptocurrency industry to operate in a regulated environment. This would not only increase transparency but also help to detect and limit the exploitation of cryptocurrency via money laundering and other criminal acts. This paves the way for the favourable development of the cryptocurrency market. Hence, this study contributes to the field of behavioral finance.

The following are the remaining sections: in the section 2, extant literature has been reviewed along with the formulation of hypothesised relationships. The section 3 entails research methodology to examine the hypotheses and validate the extended model. The section 4 of the paper includes data analysis and interpretation. The sections 5 and 6 describe the discussions and implications. The penultimate section covers conclusions, limitations, and scope for future research.

2 Conceptual framework and hypotheses development

Traditional financial markets hold assumptions, such as the unpredictability of returns (Thies and Molnár 2018) and the risk-return trade-off (Aalborg et al. 2019), for cryptocurrency, such as Bitcoin, whose returns exhibit statistically significant variances in the risk-return trade-off due to anomalous price volatility regimes (Koutmos and Payne 2021). It increases risks, reduces the stability and robustness of hedging features in this asset class, and introduces behavioral biases into the investment decision-making process of cryptocurrency (Hairudin et al. 2020; Mokni et al. 2022), which contribute to market anomalies in the crypto market such as bubbles and crashes (Singh et al. 2021). There are four phases of cryptocurrency bubbles: the stealth, awareness, mania, and blowoff phases (Hoang and Mørken 2018). Some of the behavioral biases thought to be present at each stage of the bubble include herding (stealth phase), optimism (awareness phase), overconfidence (mania phase), and loss aversion (blow-off phase) (Hidajat 2019).

This signifies that among the several potential predictors of volatility, a dearth of rationality in investment decisions cannot be ruled out as a result of behavioral biases (Cheah and Fry 2015). Hence, this study provides an overview of the relevant literature on distinct behavioral biases that impact individual investors' decision-making behavior in the crypto market in this section. To justify this phenomenon, the present study used the prospect theory (Kahneman and Tversky 1979), which focuses on investors' decisions based on risk prospects; the heuristics theory (Tversky and Kahneman 1974), which leads to investors making decisions under uncertainty; and the herding theory (Graham 1999), which emphasizes that investors rely on another investor's decision more than their own, from the literature of behavioral finance (Dar and Hakeem 2015). Ergo, the present study takes into consideration herding, loss aversion, and overconfidence as independent variables from the pertinent literature of crypto investors since these are the most prominent biases that are found among crypto investors (e.g., Singh et al. 2017; Gupta and Shrivastava 2021; Chhatwani and Parija 2023), while crypto investors' decision-making behavior is an independent variable. However, the primary emphasis of this research is to explore FOMO as a mediator in the relationship between the herding effect, loss aversion, and overconfidence and crypto investors' decision-making behavior, as depicted in Fig. 1.

2.1 Herding and crypto investment decisions

The term "herding" was originally studied in zoology and, subsequently, psychology (Haryanto et al. 2020). Herding is a process in which one economic agent imitates the decisions of others instead of acting independently (Baddeley 2010), which results in the synchronization of price co-movements of related financial assets (Caferra 2020). According to Christie and Huang (1995), when opinions converge, result variability decreases because beliefs converge to the prevalent market reaction. This tendency has historically developed during times of financial turbulence, such as the 2008 financial crisis, emphasizing the need to research how the herd instinct affects asset values in financial markets (Hälli 2022). This effect has been proven to be the most ubiquitous behavioral bias in the financial market (Kumar and Goyal 2015) in both advanced (Hwang and Salmon 2004) and emerging economies (Agarwal et al. 2011). Women are more prone to the herding effect than men (Katper et al. 2019; Akhtar and Das 2019). Numerous studies (e.g., Vidal-Tomás et al. 2019; Bouri et al. 2019; Gurdgiev and Loughlin 2020; Rubbaniy et al. 2022; Nurbarani and Soepriyanto 2022) have confirmed the significant impact of herding on crypto investors. Poyser (2018) investigated herding behavioral under symmetric and asymmetric conditions, claiming that herding drives cryptocurrency values. According to Ballis and Drakos (2020), herding was shown to be more pronounced in a bullish market. In contrast, da Gama et al. (2019) found that when the market is bearish, there is a herding effect. However, Haryanto et al. (2020) observed that herding follows the market trend. When the bitcoin price rises, herding becomes more prevalent in both bullish and bearish periods. Thus, the first hypothesis of the study is:

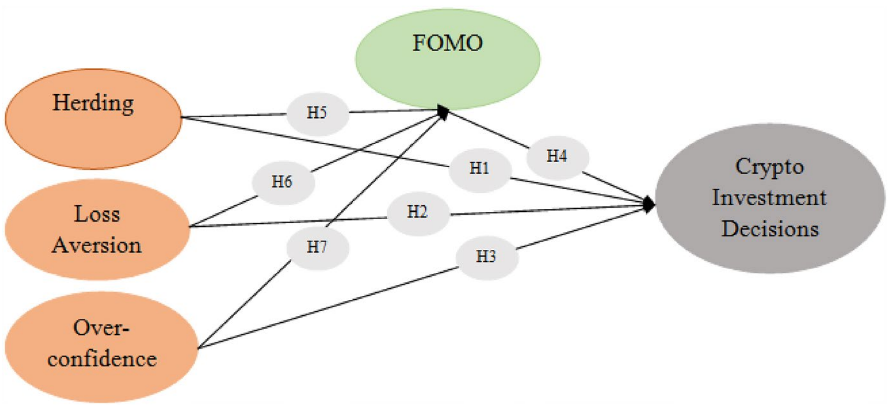

Fig. 1 Conceptual model. *Source*: Authors' Compilation

H_1 Herding has a significant influence on crypto investment decisions.

2.2 Loss aversion and crypto investment decisions

Investors are often more apprehensive about any losses they may experience as the decisions they make regarding their investments have an impact on their family's financial condition. In prospect theory, this is known as loss aversion (Barberis et al. 2003). Shefrin and Statman (1985) were the first to describe this phenomenon, claiming that most people seek to sell financial assets that have recently acquired a stronger position than those that are in a weaker position. In other words, investors prefer to sell winning assets in order to maximize gains in the probability that prices fall in the future (Dar and Hakeem 2015) because they hate losses and prefer to conserve capital rather than focus on increasing it (Jain et al. 2021). Male investors are less risk-averse than female investors (Hassan et al. 2014; Gonzalez-Igual et al. 2018). Prior studies (e.g., Popova 2019; Haryanto et al. 2020) have demonstrated that individual investors' investment decisions in the crypto market are influenced by loss aversion bias, which can manifest itself during the blow-off phase when investors who have lost money due to price drops continue to hold Bitcoin because they think that they will suffer greatly if they sell it at a loss (Hidajat 2019). Loss aversion causes disposition effects, in which investors continue to lose capital to avoid getting upset (Rau 2014). The negative disposition effect occurs when bitcoin prices have been rising (during bullish times), but the positive disposition effect occurs when bitcoin prices have been falling (during bearish periods) (Haryanto et al. 2020). Thus, the second hypothesis of the study is:

H_2 Loss aversion has a significant influence on crypto investment decisions.

2.3 Overconfidence and crypto investment decisions

Overconfidence is a phenomenon that occurs when individuals believe they know more than others (Pompian 2006). They consider their judgement superior to others' (Jain et al. 2015) and feel that they know more than they can do (Shiller 2000). Overconfidence is often related to numerous words in the economic literature, like "better-than-average effect," "illusion of control," "miscalibration," and "unrealistic optimism" (Glaser and Weber 2007). People demonstrate overconfidence in their knowledge, competence, and skills while investing in the financial market, which is inextricably linked with optimism (Poyser 2018). Many investors are optimistic regarding their knowledge of investments and overlook the risks involved (Jain et al. 2021). Women are less confident in their investment decisions than men due to a lot of societal pressure (Pulford and Colman 1997; Hira and Loibl 2008). When the price of Bitcoin reaches an all-time high during the mania phase, investors think they have superior knowledge and capacity to discern which cryptocurrencies to invest in (Hidajat 2019). As a result, they are more likely to invest in cryptocurrency (Jalal and Leonelli 2021; Kim and Hanna 2021; Sudzina et al. 2021; Nurbarani and Soepriyanto 2022). Thus, the third hypothesis of the study is:

H_3 Overconfidence has a significant influence on crypto investment decisions.

2.4 FOMO and crypto investment decisions

The term "fear of missing out" (FOMO) was coined in 2004 to characterize a behavior identified on social networking sites (Gupta and Sharma 2021), where it is associated with the dread and anxiousness of missing out on crucial information and breakthroughs due to not being constantly connected to social media (Przybylski et al. 2013). In the context of investment decisions, FOMO bias arises when investors notice that other investors are entering the market or targeting specific financial instruments, as they believe they should do the same or risk missing out on the opportunity (Hershfield 2020a, b). They are prompted by a desire to increase their earnings; therefore, they attempt not to miss out on any chance to make prospective gains (Kang et al. 2020). Hysteria erupted in the market when cryptocurrencies were unveiled, with everyone wanting to invest in these digital currencies (Denison et al. 2019). It was also found that many investors didn't have much idea about cryptocurrency, but fear of missing out caused them to invest in it blindly (Gupta and Shrivastava 2021). Ergo, FOMO does affect investing decisions, whether deliberately or unwittingly (Martin et al. 2022). There have been a few studies (e.g., Baur and Dimpfl 2018; Delfabbro et al. 2021; Zhang and Mani 2021; Martin et al. 2022; Bonaparte 2022) that discussed FOMO in cryptocurrency investment decisions. According to Zhang and Mani (2021), positive market shocks have a bigger influence on the volatility of these financial assets than negative shocks of equal magnitude due to the FOMO effect. Some studies have shown that women experience more FOMO than men (Stead and Bibby 2017; Beyens et al. 2016), although Przybylski et al. (2013) discovered the contrary. Thus, the fourth hypothesis of the study is:

$\mathbf{H_4}$ FOMO has a significant influence on crypto investment decisions.

2.5 FOMO as mediator

FOMO's relationship with herding, loss aversion, and overconfidence in various contexts has been validated by several studies in the past (e.g., Kang et al. 2020; Tarjanne 2020; Gupta and Shrivastava 2021). The authors of these studies stated that FOMO drives people to collectively consume products in order to get psychological consolation. Many individuals are more inclined to invest in investment instruments when they notice that their friends and colleagues are thriving in the financial market. As a consequence, FOMO predominates, which causes herd behavior and constantly drives financial asset prices up (Hershfield 2020a, b). Denison et al. (2019) identified FOMO as a strong driver to encourage investors to make quick investment decisions in order to keep up with their neighbors and colleagues. The author also highlighted that many investors are overly impulsive in order to get high returns immediately and avoid future losses. The presence of FOMO considerably amplifies the effect of loss aversion and herding on investors' investment decisions. This indicates that while individual investors may normally demonstrate some extent of herding effect or loss aversion while taking investment decisions, if they are predisposed to FOMO, their investment decisions will be considerably more influenced by herd behavior or loss aversion (Gupta and Shrivastava 2021). In the context of overconfidence bias, Liu (2019a, b) discovered that less confident investors are more susceptible to the FOMO effect, since people lack confidence when they are unsure of whether they should invest in a particular financial asset or not, but due to the FOMO effect, they are willing to do so. On the other side, when an investor is more confident about their investment, they continue it with the expectation that they will undoubtedly receive a high return. Thus, the projected hypotheses of the study are:

H_5 Herding has a significant influence on FOMO in crypto investment decisions.

H_6 Loss aversion has a significant influence on FOMO in crypto investment decisions.

H_7 Overconfidence has a significant influence on FOMO in crypto investment decisions.

H_8 FOMO among cryptocurrency investors mediates the relationship between herding and crypto investment decisions.

H_9 FOMO among cryptocurrency investors mediates the relationship between loss aversion and crypto investment decisions.

H_{10} FOMO among cryptocurrency retail investors does not mediate the relationship between overconfidence and crypto investment decisions.

3 Research methodology

3.1 Evaluation framework

The current study was intently interested in examining the effect of behavioral biases on investment decisions of those crypto investors who have a minimum of 2 years of investment experience in crypto market, as experienced investors make sound investment decisions based on value criteria (Korniotis and Kumar 2011) and their investment techniques may undergo significant change (Tripathi 2008). A measurement scale for the present study was devised after an extensive analysis of the pertinent literature, in which various constructs and their corresponding items were chosen. To confirm the validity of various latent constructs and their items and to certify that the dimensions of the constructs are suitably worded and understandable, the present study deployed pre-testing methods, such as semi-structured interviews of two academic experts, one financial expert, and five experienced crypto investors. Their suggestions and opinions were considered to the greatest extent possible without affecting the nature of the questions. Thenceforth, data was collected from the respondents using a 7-point Likert scale with the options of "strongly disagree" to "strongly agree."

3.2 Designing of questionnaire

To collect primary data from crypto investors, a structured questionnaire was used. The questionnaire used in the study was labelled, "The objective of this survey is to collect tangible information about how behavioral biases impact crypto investors' investment decisions." The questionnaire was divided into two sections. Section I included 8 questions related to the demographic information of the respondents, such as gender, age, education, occupation, annual income, investment experience, percentage of income invested, and frequency of investment. Section II incorporated 24 items related to various constructs of the study, namely, herding, loss aversion, overconfidence, FOMO, and cryptocurrency investment decisions, extracted from relevant literature, i.e., Gupta and Shrivastava (2021), Jain et al. (2021), Liu (2019a, b); and Luong and Thu Ha (2011) (see "Appendix"). However, in accordance with the study's aims and focus, the scale was later amended in accordance with the guidelines given by Netemeyer et al. (2003).

3.3 Data collection

Crypto investment in India is mostly driven by the Generation Z and millennial populations. According to the report of homegrown crypto exchange CoinSwitch, the vast majority of crypto investors in the nation are between the ages of 18–25 and 26–35 (CoinSwitch 2022). Therefore, the present study's population included crypto retail investors from the north Indian region, namely Jammu and Kashmir, Delhi NCR, Himachal Pradesh, Haryana, Punjab, Uttarakhand, and Chandigarh, due to its diverse culture and more young population (see Singh et al. 2017; Kaur et al. 2021). In addition, Bhaskar (2016) reported that the North Indian consumers are rich and tech savvy who easily adapt online services. Even north Indian females use more digital technology as compared to other regions (Tech2 2016). A snowball sampling technique was deployed to collect primary data. Snowball sampling is a non-probability sampling technique that is best suited for those research studies where a specific type of population is required but it is difficult to access and there is an interconnected network of people or organizations (Sood et al. 2022; Nardi 2006). In the present study, the population was of a specific type, i.e., crypto investors, and they belonged to an interconnected system of crypto exchanges. Two qualifying questions were asked at the outset of the survey: (1) Are you aware of cryptocurrency? (2) Do you have at least 2 years of experience in cryptocurrency investment? Those who responded "yes" were given access to the whole questionnaire. A total of 689 individual crypto investors of different ages, geographies, and investment corpuses were solicited physically and electronically (via email, WhatsApp, and Telegram) during a four-month period, from July 2022 to October 2022. In addition, several personal and telephone interviews were carried out to help respondents better comprehend the concepts and questions by taking time from them at their convenience. Regular reminders were also sent out to ensure that the data was collected on time. A total of 541 crypto investors responded positively to the questionnaire, out of which 68 were found to be incomplete or invalid. Therefore, it has been removed from the final analysis. The remaining 473 responses are considered for final analysis, resulting in a response rate of 68.65% (as shown in Table 1). It has been documented that the Cochran (1963) formula was used to calculate sample size, which is acceptable when the population is large or infinite (Israel 1992). Further, to confirm the appropriateness of the sample size, G*Power (Faul et al. 2009) was used, which indicated 125 as the minimum sample required to attain statistical power of 99%. Similar researchers in the past (e.g., Sharma et al. 2022) have also conducted their study in the crypto domain with an approximate similar sample size.

3.4 Participants description

Male investors composed 79.7% of the 467 respondents, while female investors accounted for the remaining 20.3%. Furthermore, the majority of investors, 43.3%, were found to be between the ages of 30–40. This reveals that the crypto investment market is dominated by young and male investors, which is consistent with Steinmetz et al. (2021)'s and Auer and Tercero-Lucas (2022)'s findings, who reported that the majority of crypto investors are young and male. In addition, 49% of respondents were postgraduates, while 36.6% were graduates. Furthermore, 49.2% of respondents were self-employed, while 33% were salaried. In terms of annual income, 35.3% of respondents earn between 10 to 15 lakhs, while 26% earn between 5 to10 lakhs. This suggests that highly qualified investors with good earnings are more likely to invest in cryptocurrencies. When it comes to investment experience, 85.6% of investors have 2 to

Table 1 Participants' description (n = 473). *Source*: Authors' compilation

Variables	Category	Frequency	Percentage
Gender	Male	377	79.7
	Female	96	20.3
Age (in years)	18–30	90	19.0
	30–40	205	43.3
	40–50	130	27.5
	50–60	43	9.1
	60 and above	5	1.1
Qualification	High School or equivalent	16	3.4
	Diploma or equivalent	40	8.4
	Graduate or equivalent degree	173	36.6
	Postgraduate or equivalent degree	232	49.0
	Others	12	2.6
Employment	Salaried	156	33
	Self-employed/businessman	233	49.2
	Unemployed/retired/student	76	16
	Others	8	1.8
Annual Income (in ₹)	Less than 500,000	64	13.5
	500,000–10,00,000	123	26
	10,00,000–15,00,000	167	35.3
	15,00,00–20,00,000	93	19.7
	20,00,000 and above	26	5.5
Investment experience (in years)	2–5	405	85.6
	5–10	56	11.9
	10 and above	12	2.5
Percentage of Income Invested	Less than 10%	53	11.2
	10–20%	246	52
	20–30%	98	20.8
	30–40%	51	10.8
	40% and above	25	5.2
Frequency of investment	Monthly	276	58.3
	Quarterly	147	31.0
	Semi Annual	45	9.6
	Annual	5	1.1

5 years of experience. This implies that the subjects of research are experienced in the crypto market. This ensured more consistent outcomes, as experience has a positive influence on investment skills (Korniotis and Kumar 2011). Additionally, 52% of respondents reported that they are investing approximately 10% to 20% of their incomes in the crypto market. Another intriguing conclusion was that the majority of investors, i.e., 58.3%, invest in cryptocurrencies on a monthly basis. This shows that the preponderance of investors in the cryptocurrency market are active investors. A detailed description of the participants is presented in Table 1.

4 Data analysis and interpretation

4.1 Common method bias

While carrying out behavioral studies, when data for both endogenous and exogenous constructs is collected through a single instrument, it is a must to check the presence of common method bias (CMB) problem (Kock 2015). In the present study, CMB was measured using a Harman single factor, in which all the items of endogenous and exogenous constructs were loaded into a single factor using exploratory factor analysis, which takes into account variances of less than 50% (Streukens et al. 2017). Using unrotated principal component analysis, it was found that a single factor made up of all the items explained 41.938% of the variance in the current study. This shows that there is no CMB.

4.2 Measurement model assessment

The measurement model of the present research has five latent constructs: herding, loss aversion, overconfidence, FOMO, and investment decisions (as shown in Fig. 2). In the measurement model, reliability and validity of exogenous and endogenous variables were assessed using SmartPLS (version 4.0.8.7), which includes indicator reliability, construct reliability, convergent validity, and discriminant validity. Indicator reliability is acquired by squaring the outer loadings of reflective constructs, which describe the relationship between the latent variables and their measurements (Ringle et al. 2015). When the outer loadings of all items are above the threshold value of 0.708 (Hair et al. 2016), indicator reliability is assured, as shown in Table 2. To test construct reliability, composite reliability, and Cronbach's alpha were determined; the values of both should be in the range of 0.7 and 0.95 (Diamantopoulos et al. 2012). This was assured in the current study since the Cronbach's alpha and composite reliability values were both within the prescribed range. For establishing convergent reliability, the average variance extracted (AVE) was found by averaging the square of each construct's outer loadings, which must be greater than 0.5

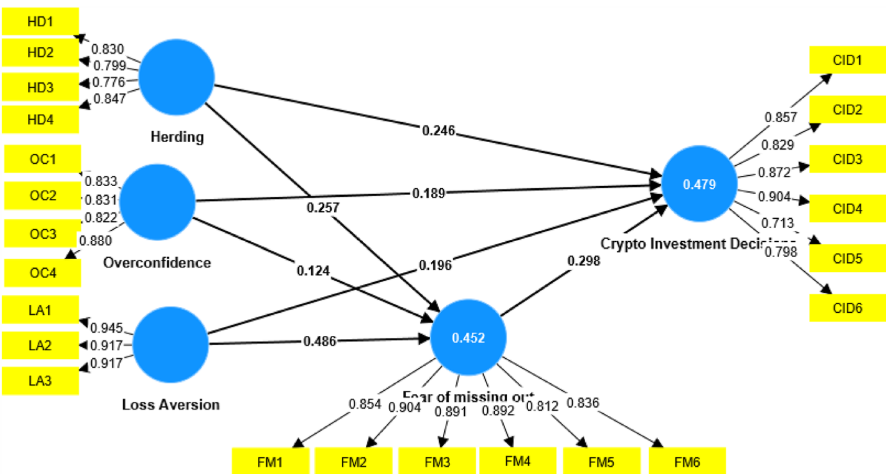

Fig. 2 Measurement model

Table 2 Measurement model assessment. *Source*: Authors' Compilation

Construct	Items	Measurement items	Outer loadings	Cronbach's alpha	Composite reliability	AVE
Herding (HD)	HD1	Other investors' decisions to choose cryptocurrency have an impact on my investment decisions	0.83	0.829	0.887	0.66
	HD2	Other investors' decisions regarding cryptocurrency volume have an impact on my investment decisions	0.799			
	HD3	I usually react quickly to the changes in other investors' decisions and follow their reactions to the crypto market	0.776			
	HD4	Other investors' decisions on buying and selling crypto currencies have an impact on my investment decisions	0.847			
Loss aversion (LA)	LA1	When faced with a sure gain, I am a risk-averse	0.945	0.917	0.948	0.86
	LA2	When faced with a sure loss, I am a risk-taker	0.917			
	LA3	I avoid selling those cryptocurrencies that have decreased in value and readily sell those cryptocurrencies that have increased in value	0.917			
Overconfidence (OC)	OC1	I believe that my skills and knowledge of the crypto market can help you outperform the market	0.833	0.866	0.907	0.71
	OC2	I know the best times to enter and exit my investment position in the crypto market	0.831			
	OC3	I feel more confident in my own investment opinion than in the opinions of my family members, friends, and colleagues	0.822			
	OC4	I trade frequently in cryptocurrency than other people	0.88			

Table 2 (continued)

Construct	Items	Measurement items	Outer loadings	Cronbach's alpha	Composite reliability	AVE
Fear of missing out (FOMO)	FM1	It upsets me when I don't hear any news about my crypto investments	0.854	0.933	0.947	0.75
	FM2	I would like to get quick updates on the trends of the cryptocurrencies in which I have invested	0.904			
	FM3	It bothers me when I miss out an investment opportunity in cryptocurrency	0.891			
	FM4	I'm afraid of being the last to hear about significant news that is relevant to my crypto portfolio	0.892			
	FM5	The more I see values of cryptocurrency sky rocketing the more I don't want to miss out on the gains	0.812			
	FM6	Cryptocurrency is a new way to make me a millionaire	0.836			
Crypto investment decisions	CID1	In general, I am satisfied with my cryptocurrency investment decisions	0.857	0.909	0.93	0.69
	CID2	My crypto investment decisions help me to achieve my investment objectives	0.829			
	CID3	I believe that I can make crypto investment decisions accurately	0.872			
	CID4	I mostly earn more than the average return generated by the crypto market	0.904			
	CID5	I make all the crypto investment decisions at my own	0.713			
	CID6	Return on my crypto portfolio justifies my investment decisions	0.798			

Table 3 HTMT criterion. *Source*: Authors' compilation

	Crypto investment decisions	FOMO	Herding	Loss aversion
FOMO	0.633			
Herding	0.594	0.532		
Loss aversion	0.54	0.643	0.409	
Overconfidence	0.439	0.318	0.397	0.222

Table 4 Fornell and Larcker criterion. *Source*: Authors' compilation

	Crypto investment decisions	FOMO	Herding	Loss aversion
Crypto investment decisions	**0.831**			
FOMO	0.591	**0.866**		
Herding	0.523	0.474	**0.813**	
Loss aversion	0.5	0.602	0.358	**0.926**
Overconfidence	0.403	0.305	0.346	0.19

The values in bold represent square root of AVE

(Fornell and Larcker 1981). This was confirmed by the fact that the AVE of all constructs was greater than 0.5, as shown in Table 2.

Further, the discriminant validity of the model was analysed using two criteria (Table 3). The first criteria is to check the heterotrait-monotrait (HTMT) criterion, which should be less than 0.85 for all constructs (Henseler et al. 2016), displayed in Table 3, which confirms the discriminant validity of the constructs. Another criterion suggested by Fornell and Larcker (1981) was also used to assess discriminant validity. In this method, correlation among constructs should be less than the square root of AVE for every construct (Ringle et al. 2015), which was achieved as shown in Table 4.

4.3 Structural model assessment

Before testing a hypothesis, the first step in evaluating a structural model is to look at issues of multicollinearity. Diamantopoulos and Siguaw (2006) stated that high intercorrelation between variables is the main cause of multicollinearity in any model. Variance inflation factor (VIF) is the standard approach for determining if a model has multicollinearity issues (Diamantopoulos and Siguaw 2006). The values of VIF must be less than 5, which is a reliable indicator of the truancy of multicollinearity issues in a model (Hair et al. 2017). In this study, all of the VIF values for the predictor variables were less than 5, which shows that there were no issues of multicollinearity in the inner model. The second step is to put the study's hypotheses to the test through the bootstrapping technique in SmartPLS. Bootstrapping is a resampling technique performed with a subsample size of 5,000 since a large sample size assures reduced variance between the original and mean values of regression path coefficients. Besides, it helps in ensuring the stability of estimates (Davcik 2014). Ergo, it generated path coefficients, *p* values, and t-statistics, which are displayed in Table 5.

Table 5 Path analysis. *Source*: Authors' compilation

Hypotheses	Path	Path coefficient	t-statistics	*P* value	VAF	Decision
H1	HD->CID	0.246	4.614	0	–	Supported
H2	LA->CID	0.196	4.313	0	–	Supported
H3	OC->CID	0.189	3.726	0	–	Supported
H4	FOMO->CID	0.298	6.322	0	–	Supported
H5	HD->FOMO	0.257	6.022	0	–	Supported
H6	LA->FOMO	0.486	12.721	0	–	Supported
H7	OC->FOMO	0.124	3.262	0.001	–	Supported
H8	HD->FOMO->CID	0.077	4.56	0	23%	Supported
H9	LA->FOMO->CID	0.145	5.242	0	42.50%	Supported
H10	OC->FOMO->CID	0.037	3.044	0.002	16.30%	Supported

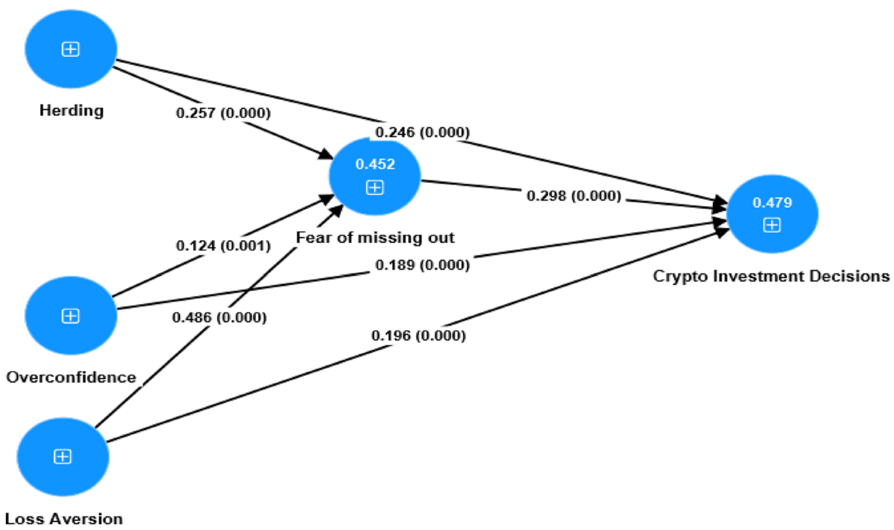

Fig. 3 Structural model

The structural model of the research is displayed in Fig. 3. The study's results showed that all four behavior biases—herding (HD), loss aversion (LA), overconfidence (OC), and fear of missing out (FOMO)—have a positive and significant effect on crypto investment decisions (CID), which supports *H1, H2, H3, and H4* (as shown in Table 5). In this context, FOMO (b = 0.298, t = 6.322) has the greatest influence on crypto investment decisions among the four biases, followed by HD (b = 0.246, t = 4.575), LA (b = 0.196, t = 4.26), and OC (b = 0.189, t = 3.726). As far as *H5, H6,* and *H7* are concerned, full statistical support was found for all of them, which stated that all three behavioral biases, i.e., HD, LA, and OC, were found to have a significant positive impact on FOMO. Out of them, LA (b = 0.486, t = 12.721) has the most substantial influence of FOMO, followed by HD (b = 0.257, t = 6.022) and OC (b = 0.124, t = 3.262). To analyze the mediating effect of FOMO on the relationship between behavior biases, namely, herding, loss aversion, and overconfidence bias, and crypto investment decisions, Nitzl et al. (2016), Carrión et al. (2017), and Hair et al. (2017) guidelines were followed in the present study.

The indirect effects of HD (b = 0.077), LA (b = 0.145), and OC (b = 0.037) were found to be significant, as shown in Table 5. The total effect of HD on CID was also significant, with b = 0.323 and t = 6.006. Similarly, the total effect of OC (b = 0.226, t = 4.468) and LA (b = 0.341, t = 7.167) on CID was also found to be significant. The strength of the mediation as per guidelines given by Nitzl et al. (2016) was analyzed, and Variance Accounted For (VAF) values (shown in Table 5) were also calculated by dividing indirect effect by total effect for every relationship. If VAF is less than 20%, nearly zero mediation occurs; if VAF is greater than 20% but less than 80%, it could be characterized as a typical partial mediation; and a VAF above 80% indicates a full mediation (Nitzl et al. 2016). Hence, in the present research, VAF values conclude partial mediation in the case of LA and HD, whereas FOMO was not found to be mediating the relationship between OC and CID as the VAF value is less than 20%. The signs of direct and indirect effects for both HD and LA are positive. As a result, a complementary partial mediation of FOMO bias on the relationship between HD, LA and CID has been established.

When the impact of LA, HD, and OC on CID was checked without using FOMO as a mediator, R^2 was found to be 43%. The addition of FOMO as a mediator to the model increased R2 to 0.479, indicating that 48% of the variance in CID is explained by HD, LA, OC, and FOMO, indicating good predictive precision of the model (Hair et al. 2019). Further Q^2 and PLS predict were analyzed to assess the predictive relevance of the model as per the guidelines given by Shmueli et al. (2019), and the results are shown in Table 6. Q^2 predict values for the PLS model are greater than 0 for all items of CID, the endogenous construct. PLS RMSE values should be compared with LM RMSE values if PLS MV prediction errors of endogenous constructs are symmetric; otherwise, PLS MAE values should be compared with LM MAE values to check the predictive relevance of the model (Shmueli et al. 2019). PLS MV prediction errors (as shown in Fig. 4) were analysed for all indicators of CID and found to be non-symmetric by observation. Hence, PLS MAE values were compared with LM MAE values for all indicators of CID. The results are displayed in Table 6. If PLS values are greater than LM values for all the indicators, then the model shows high predictive power, whereas if it happens for half or more than half of all indicators, medium predictive power is proved (Shmueli et al. 2019). For half of the indicators, PLS MAE values were smaller than LM MAE values, signifying medium predictive relevance of the model (Shmueli et al. 2019).

Table 6 Results of PLS predict. *Source*: Authors' compilation

Indicators	PLS Q^2_predict	PLS MAE	LM MAE
CID1	0.397	0.622	0.596
CID2	0.267	0.690	0.674
CID3	0.319	0.690	0.694
CID4	0.344	0.679	0.683
CID5	0.16	0.729	0.724
CID6	0.228	0.805	0.806

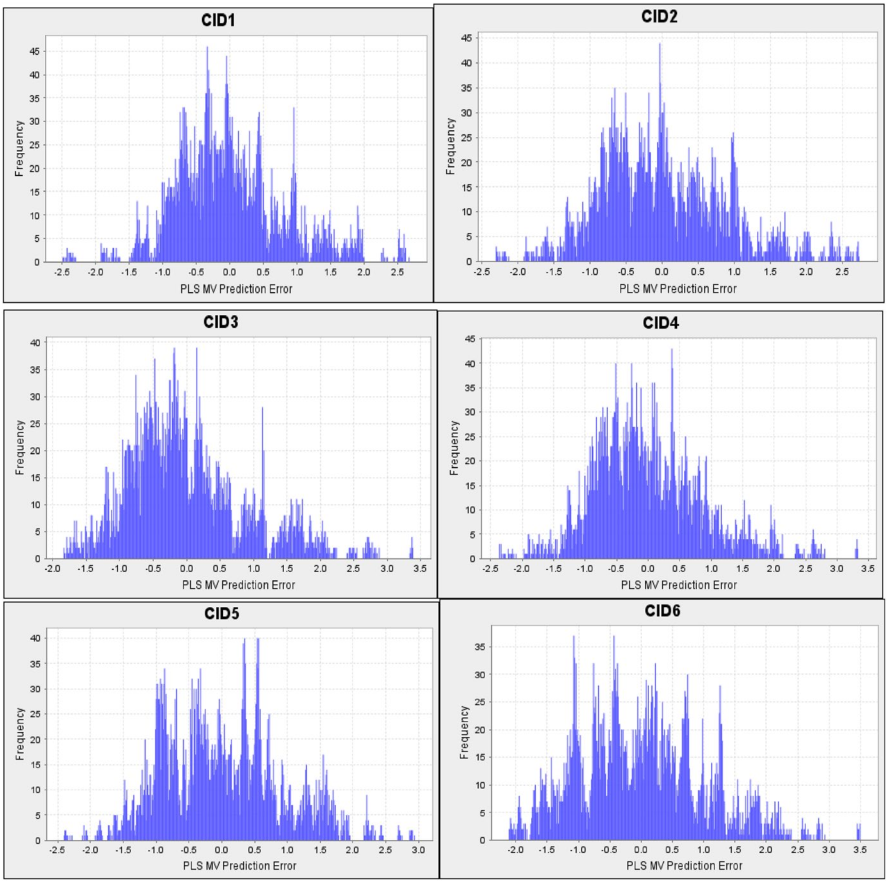

Fig. 4 PLS MV prediction errors for indicators of Crypto investment decisions

4.4 Robustness check

To check the robustness of the specified model, the guidelines mentioned by Sarstedt et al. (2020) were followed. Results of any research are considered robust if non-linearity and endogeneity are not present in the model. Thus, firstly, potential nonlinearities were checked in the structural model relationships. The quadratic effects of HD, OC, and LA on CID, as well as FOMO and the effects of FOMO on CID, were represented by interaction terms. Bootstrapping was run with 5000 subsamples. The interaction effects of all exogenous constructs, i.e., HD (p value = 0.420), OC (p value = 0.100), and LA (p value = 0.27) on FOMO were found to be insignificant. Similarly, the interaction effects of all exogenous constructs on CID were found to be insignificant, including HD (p value = 0.128), OC (p value = 0.63), LA (p value = 0.15), and FOMO (p value = 0.821). Non-linear relationships were not found in the model because the quadratic effects for all constructs were insignificant. Secondly, the model was checked for endogeneity. For this Park and Gupta's (2012), Gaussian Coupla approach was used. All combinations of Gaussian copulas included in the model were checked, and none were found to be significant (as shown in Table 7). Hence,

Table 7 Assessment of endogeneity test using the Gaussian copula approach

Test	Construct	Coefficient	*p* value
Gaussian copula of model 1 (HD)	HD	0.073	0.833
Gaussian copula of model 2 (OC)	OC	−0.281	0.159
Gaussian copula of model 3 (LA)	LA	0.212	0.245
Gaussian copula of model 4 (FOMO)	FOMO	0.022	0.89
Gaussian copula of model 5 (HD and OC)	HD	0.116	0.738
	OC	−0.289	0.155
Gaussian copula of model 6 (OC and LA)	OC	−0.297	0.141
	LA	0.223	0.219
Gaussian copula of model 7 (LA and FOMO)	LA	0.219	0.226
	FOMO	0.058	0.71
Gaussian copula of model 8 (FOMO and HD)	FOMO	0.018	0.914
	HD	0.069	0.846
Gaussian copula of model 9 (HD, OC and LA)	HD	0.093	0.794

it can be concluded that endogeneity is not present in this study, which supports the robustness of the structural model results of the present research (Hult et al. 2018). Ergo, robustness was ensured in terms of nonlinear effects and endogeneity.

5 Discussions

The study has undertaken the effort to examine how herding, loss aversion, overconfidence, and FOMO affect the investment choices made by cryptocurrency investors. Although there is a dearth of primary research on the behavior biases that influence the investment choices of crypto investors, this study goes a step further by conducting a field survey and analyzing the mediating effect of FOMO in the relationship between herding, loss aversion, overconfidence, and the decision-making behavior of crypto investors. The current study’s findings show that all four variables have a considerable effect, with FOMO having the strongest influence on the investment decisions of crypto investors, followed by herding, loss aversion, and overconfidence, respectively. In the context of FOMO, respondents of the study have opined that when they see other investors entering the cryptocurrency market, it makes them feel pushed to do the same so as not to miss out on the lucrative returns that others are obtaining. This tendency leads individuals to invest without thinking critically, and they occasionally drown. This finding is consistent with previous research studies (e.g., Baur and Dimpfl 2018; Delfabbro et al. 2021; Zhang and Mani 2021; Bonaparte 2022; Martin et al. 2022).

The study outcome has also stated that herding is rapidly growing in the cryptocurrency market as a result of market stress, significant price volatility, a lack of quality information, and cryptocurrency investors’ expectations of unprecedented positive returns. This suggests that cryptocurrency investors do not make investment decisions in isolation. Instead, they discuss cryptocurrency investment with folks that have the most influence on their thinking process and are easily influenced by them. Many investors believe that if the majority of investors’ decisions are sound, they will experience substantial returns and avoid losses; therefore, they base their investment decisions on how other investors choose to hold their cryptocurrency holdings. This finding is consistent with previous research studies (e.g., Vidal-Tomás et al. 2019; Bouri et al. 2019; Gurdgiev and Loughlin 2020; Rubbaniy et al. 2022; Nurbarani and Soepriyanto 2022). Moreover, respondents of the study have opinionated that whenever they get a chance to earn a potential gain, they become risk averse due to cryptocurrency market volatility and book the profit. On the other hand, they recognise that whenever they face losses, they are putting themselves at unnecessary risk. In short, they are generally more inclined toward avoiding losses than earning profits. As a result of their hasty decisions in the cryptocurrency market in order to minimise losses, investors suffer massive losses. This finding is consistent with Popova (2019) and Haryanto et al. (2020).

Additionally, the study's results have indicated that cryptocurrency investors are also overconfident in their investment decisions. Overconfidence is unquestionably connected to risky crypto investments, and overconfident individuals are lured into high-risk endeavours since they think that they know when to enter or exit the crypto market. Besides, they are overly optimistic about their skills in a certain scenario. However, overconfident investors do not prepare for any type of uncertainty, which puts them at risk of large losses sometimes (Jain et al. 2021). Various research studies (e.g., Kim and Hanna 2021; Jalal and Leonelli 2021; Sudzina et al. 2021; Nurbarani and Soepriyanto 2022) are consistent with this finding of the present study. Additionally, the present study has a substantial focus on the mediating effect of FOMO bias on the relationship between herding, loss aversion, overconfidence, and crypto investment decisions. In this regard, the findings of the research indicated that herding, loss aversion, and overconfidence play a substantial role in crypto investment decisions even in the absence of FOMO. However, because of the presence of FOMO bias, the impact of herding and loss aversion biases on crypto investment decisions has been greatly amplified, while the impact of overconfidence has not. The reasoning behind this finding is that because FOMO causes market deception, one should invest in cryptocurrencies; otherwise, they will miss out on earning a return. As a result, individuals are beginning to follow other people more and act on their recommendations. Furthermore, due to FOMO bias, many crypto investors become extremely aggressive in order to gain large profits quickly and prevent future losses. Overconfident crypto investors, on the other hand, are sure that they will do better than where they invest, so they don't worry about missing any opportunities.

6 Implications

6.1 Theoretical implications

Over the past many years, behavioral finance has led to a better understanding of actual investor behavior and real-world market practices, and it is likely to make substantial future developments (Delfabbro et al. 2021). Consequently, the study broadens theoretical contributions in the realm of behavioral finance and related theories, such as prospect, heuristic, and herding, by extending an understanding of how investors behave while investing in the cryptocurrency market with the additional element of FOMO. Herding, loss aversion, and overconfidence biases cause behavioral anomalies in the crypto market since investors rely on collective information and neglect real facts when making investments. Ergo, a better understanding of these critical biases and investors' behavior due to the presence of FOMO bias fills a gap in the present research. Furthermore, the current study adds new insights to traditional quantitative models such as the modern portfolio theory (MPT), efficient market theory (EMT), arbitrage pricing theory (APT), and capital asset pricing model (CAPM), which assume that individual investors make perfectly rational decisions. However, in the real world, no perfect rationality exists no matter how much experience an investor has, since rationality is limited when an individual makes investment decisions due to cognitive limitations such as limitations of knowledge, resources, computational capacity, and time constraints, as well as the emotional biases of the decision-makers, which are tricky to control or change, especially during market turbulence (Pompain 2012). Thus, this research encourages all types of cryptocurrency investors and financial experts to recognize that understanding behavioral finance concepts and theories is critical for understanding the decision-making behavior of crypto investors.

6.2 Practical implications

This study has practical implications for individual and institutional cryptocurrency investors, crypto portfolio managers, policymakers, researchers, market regulators, and society at large. First, the findings of the present study enable investors to comprehend how their own psychological factors influence their choice of investments. Hence, when selecting investment avenues, cryptocurrency investors should take into consideration the influence of critical biases such as herding, loss aversion, overconfidence, and FOMO. This can increase their understanding of the possible financial pitfalls of cryptocurrency caused by behavior biases, which would aid in achieving an optimal return on investment and avoiding any potential errors in judgment. Second, this study helps crypto portfolio managers who keep an eye on bitcoin and many altcoins figure out which behavior biases affect cryptocurrency investors the most. This lets them give their clients the best investment advice. Third, this research provides policymakers with valuable information and expertise on the behavioral aspects of individual investors, helping them to make the best decisions and methods for crypto investors to enhance cryptocurrency investment among Indian investors. Policymakers would be better equipped to judge the necessity of cryptocurrency regulations if they understood how investors make decisions. Fourth, the study is useful for both researchers and academicians because it helps them to understand them how distinct psychology of cryptocurrency investor. Fifth, this research helps the market regulators to make stronger laws and regulations that are required to limit the influence of behavior biases on crypto investors' decision-making and offer investors a more secure investing environment. These laws ultimately help the Indian government with the enactment of comprehensive policy announcements that allow the cryptocurrency industry to operate in a regulated environment (Tambe and Jain 2023). In this regard, the Finance Ministry has taken a comprehensive step by including cryptocurrency under the ambit of the "Prevention of Money Laundering Act" (PMLA) (Chadha 2023). This implies that custodians, exchanges, and wallet providers, among others, engaged in crypto-related trade will be subject to the PMLA (Chadha 2023). Due to this law, crypto companies will now be required to carry out their operations with more due diligence, which can help keep the crypto market stable and lower the risk for investors in cryptocurrencies in the long run. This would not only increase transparency but also help to detect and limit the exploitation of cryptocurrency via money laundering and other criminal acts. This paves the way for the favourable development of the cryptocurrency market. It may help stop people from speculating on cryptocurrency, which would control behavioral biases and make cryptocurrency a good way to invest that adds to the gross domestic product (GDP) and helps society.

7 Conclusion, limitations, and scope for future research

Since the RBI lifted its ban on investing in cryptocurrencies in March 2020, there has been a huge increase in them. Indian exchanges have seen a lot of new users join, and their daily trading volumes keep going up (Saundal 2021). Even though investing in cryptocurrencies has gone through the roof, it is very risky and has a high risk-to-reward ratio (Fonseca et al. 2019). One of the main reasons why cryptocurrency prices change a lot is because of how investors' emotions affect their decisions. In this context, the current study looked at the most significant behavioral factors, like herding, loss aversion, overconfidence, and fear of missing out (FOMO), that affect how cryptocurrency investors choose to invest their money. The study has also looked at how FOMO affects herding, loss aversion, overconfidence, and the decisions people make about investing in crypto. The results of the study showed that each of the four biases has a big effect on how cryptocurrency investors choose where to put their money. Unexpectedly, FOMO has turned out to be the most influential bias, followed by herding, loss aversion, and overconfidence, in that order. In addition, FOMO bias establishes a complementary partial mediation between herding, loss aversion, overconfidence, and crypto investment decisions. In conclusion, this study has shown that behavioral factors, when combined with other factors, are an important phenomenon that should be studied regularly to understand how crypto investors make decisions, since these factors affect the investors' portfolios, the market, and the economy as a whole.

However, there are certain limitations attached to the present study. First, the data has been collected from those individuals who have invested continuously in cryptocurrencies for at least two years; hence, only experienced participants were included in this study. A future study might be conducted on novel investors as well. Second, the study was confined to individual crypto investors in one country, India, and one financial market. Therefore, there is a need to exercise caution when projecting the findings to other regions. Future research might be undertaken in overseas markets with different populations, such as professional crypto investors. Third, the study's findings are based on a sample of north Indian crypto investors. As a result, future research may be undertaken using countrywide data. Fourth, the study solely looked at the herding effect, loss aversion, and overconfidence. Other heuristics and prospect biases can be studied in the future to see how they affect cryptocurrency investment decisions in the presence of FOMO bias. In addition, a moderating variable such as gender, income, frequency of investment, etc., might be put into the model to see if moderated mediation is possible. Fifth, the study has been conducted with a sample size of 473 respondents. Although the sample size is appropriate, a larger sample size should be employed for future studies that reflect the more realistic scenario of the Indian crypto market.

Appendix: Questionnaire

Section I: demographic profile of the respondent

1. Kindly indicate your gender: Male ☐ Female ☐
2. Please select your age range (in years): 18-30 ☐ 30-40 ☐ 40-50 ☐ 50-60 ☐ 60 & above ☐
3. What is your highest level of education?
   High School or equivalent ☐ Diploma or equivalent ☐ Graduate or equivalent degree ☐ Post Graduate or equivalent degree ☐ Others ☐
4. Please select your occupation status
   Salaried ☐ Self-Employed/ Businessman ☐ Unemployed/student/retired ☐ Others ☐
5. Please select your annual income (in ₹)
   Less than 500,000 ☐ 500,000-1000,000 ☐ 1000,000-1500,000 ☐ 1500,000-2000,000 ☐
   2000,000 & above ☐
6. How long you have been investing in the crypto market (in years)?
   2 to 5 ☐ 5 to 10 ☐ 10 & above ☐
7. What percentage of your investment portfolio is invested in the stock market?
   Less than 10% ☐ 10% - 20% ☐ 20% - 30% ☐ 30% - 40% ☐ 40% & above ☐
8. How frequently do you invest in the stock market?
   Monthly ☐ Quarterly ☐ Semi-annually ☐ Annually ☐

Section II: survey Questions

The following questions are connected to how behavioral biases like herding, loss aversion, and herding impact the decision-making behavior of crypto investors in the presence of FOMO as a mediator. Please indicate your level of agreement/disagreement with the following statements on a scale of 1–7, where 1 indicates "strongly disagree", 2 indicates "disagree", 3 indicates "somewhat disagree", 4 indicates "neither agree nor disagree", 5 indicates "somewhat agree", 6 indicates "agree", and 7 indicates "strongly agree."

S. no.	Statements	1	2	3	4	5	6	7
1	Other investors' decisions to choose cryptocurrency have an impact on my investment decisions							
2	Other investors' decisions regarding cryptocurrency volume have an impact on my investment decisions							
3	I usually react quickly to the changes in other investors' decisions and follow their reactions to the crypto market							
4	Other investors' decisions on buying and selling crypto currencies have an impact on my investment decisions							

S. no.	Statements	1	2	3	4	5	6	7
5	When faced with a sure gain, I am a risk-averse							
6	When faced with a sure loss, I am a risk-taker							
7	I avoid selling those cryptocurrencies that have decreased in value and readily sell those cryptocurrencies that have increased in value							
8	I believe that my skills and knowledge of the crypto market can help you outperform the market							
9	I know the best times to enter and exit my investment position in the crypto market							
10	I feel more confident in my own investment opinion than in the opinions of my family members, friends, and colleagues							
11	I trade frequently in cryptocurrency than other people							
12	It upsets me when I don't hear any news about my crypto investments							
13	I would like to get quick updates on the trends of the cryptocurrencies in which I have invested							
15	It bothers me when I miss out an investment opportunity in cryptocurrency							
16	I'm afraid of being the last to hear about significant news that is relevant to my crypto portfolio							
17	The more I see values of cryptocurrency sky rocketing the more I don't want to miss out on the gains							
18	Cryptocurrency is a new way to make me a millionaire							
19	In general, I am satisfied with my cryptocurrency investment decisions							
20	My crypto investment decisions help me to achieve my investment objectives							
21	I believe that I can make crypto investment decisions accurately							
22	I mostly earn more than the average return generated by the crypto market							
23	I make all the crypto investment decisions at my own							
24	Return on my crypto portfolio justifies my investment decisions							

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Declarations

Conflict of interest All authors declare that they have no conflicts of interest.

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