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Print ISSN: [3006-2497](#) Online ISSN: [3006-2500](#)Platform & Workflow by: [Open Journal Systems](#)**Impact of Behavioral Aspects on Crypto-Currency Investment Decisions in Baluchistan****Dawood Ali**

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Bilal.sarwar@buitms.edu.pk**Abstract**

This study examines the influence of behavioral factors on crypto-currency investment decisions, focusing on five dimensions: investor sentiment, overconfidence, salience, overreaction, and herding behavior. A quantitative causal research design was employed, with primary data collected from 100 respondents through a structured questionnaire using a non-probability convenience sampling technique. Data were analyzed using SPSS, employing reliability analysis, descriptive statistics, correlation analysis, and regression analysis. The results indicate that behavioral factors collectively explain approximately 52.6% of the variation in crypto-currency investment decisions ($R^2 = 0.526$, $F = 20.872$, $p < .001$). Overconfidence emerged as the strongest positive predictor ($\beta = 0.451$, $p < .001$), followed by herding behavior ($\beta = 0.275$, $p = .001$) and investor sentiment ($\beta = 0.272$, $p = .001$). Salience exhibited a significant negative effect ($\beta = -0.202$, $p = .011$), while overreaction did not significantly influence investment decisions ($\beta = -0.031$, $p = .709$). The findings reveal that crypto-currency investment decisions are not driven solely by rational financial considerations but are substantially shaped by psychological biases and emotional factors. These results have important implications for investor education, financial literacy programs, and regulatory policy in the developing crypto-currency market.

Keywords: behavioral finance, crypto-currency, investment decisions, overconfidence, herding behavior

1. Introduction

Crypto-currency is a form of digital cash that can be used in decentralized systems and operates through block-chain technology. Unlike traditional government issued currencies such as US dollars or euros, crypto-currencies operate with no central authority (such as a bank) and rely on digital security work. The decentralized architecture reduces costs since there is no intermediary and transactions take place between users on the network providing additional transparency. Priced volatility and the regulatory

challenges notwithstanding, crypto-currencies are growing in popularity because they enable financial inclusion; permit cross-border transactions that remain officially prohibited under incumbent banking regulations, and promise to create new applications beyond those traditional finance is able - or willing. Crypto-currencies are based on block chain technology - a distributed and decentralized ledger. It is a series of blocks that consists the transaction lists. This protects openness, security and the longevity of information transactions (Johnson, Sun, Stjepanović, Vu, & Chan, 2023; Pelster, Breitmayer, & Hasso, 2019).

The operating system for crypto-currencies is a decentralized network of computers, or nodes. This shows that no one organization, like the government or a banking organization, controls the entire currency. Decentralization increases security and decreases the need for middlemen in financial transactions. Cryptography utilize by crypto-currencies to prevent the generation of upcoming units and secure transactions. To facilitate secure transactions and control access to bitcoin holdings, the process uses public and private keys. A process known as mining is also used by some crypto-currencies, similarly Bitcoin, to validate transactions and add them to the block chain, a distributed ledger. In return for their computing labor, miners that participate in this process are rewarded with newly created bitcoin coins. Throughout the mining process, complex mathematical puzzles must be solved to protect the network and guarantee the accuracy of transactions carried out inside the bitcoin ecosystem (Delfabbro, King, & Williams, 2021).

Many crypto-currencies limit the total amount of coins that can be created within their ecosystem to create the illusion of scarcity. The original crypto-currency, Bitcoin, for example, has only 21 million units in circulation. This supply limitation is in stark contrast to traditional fiat currencies, which are susceptible to central bank-induced inflationary pressures. Decline in Bitcoin price dynamics plays an important role because only a limited amount can increase prices in combination with increasing demand. An example of this is the situation with Bitcoin (Johnson, Co, et al., 2023). Because it essentially prevents value dilution and promotes a narrative about crypto-currencies acting as a store of wealth, similar to precious metals like gold, investors often attribute this decline to crypto-currencies. See as a major component supporting the long-term value proposition of crypto-currencies (Sonkurt & Altınöz, 2021).

With digital wallets, users may securely store and manage their bitcoin holdings. These wallets can be either hardware or software based. Software wallets are more practical and may be accessed through programmers or internet platforms, whereas hardware wallets keep private keys offline on actual devices to improve security. Printing their keys on paper is a choice made by some users who want to boost redundancy and defend against online threats. Wallets are therefore essential for enabling users to deal with crypto-currencies while preserving ownership and security of their assets (Hussain, Hassan, Khan, & Khan, 2025).

1.1. Research objectives

- To determine the impact of behavioral aspect on crypto currency investment decision
- To identify which behavioral aspect is considered to make crypto currency investment decision

2. Literature Review

The research explores the motivations of crypto-currency traders and whether they are motivated by a conscious strategy to diversify into a new potential asset class or are simply part of an overall strategy of increasing risk-taking. The study focuses on a sample of 96,054 individual accounts from an online broker that allows its customers to trade contracts for difference (CFD) on a wide range of underlying products, including equities and crypto-currencies. The findings reveal that when investors begin trading crypto-currencies, they increase their risk-taking on the stock market. Specifically, investors that enter crypto markets concurrently increase their risk-taking in stock trading, increasing the frequency of trades and leverage, resulting in worse profits. According to the study, bitcoin traders are motivated by risk-taking behavior (Aydin, Ağan, & Aydin, 2021).

This research investigates the psychology of crypto-currency trading, looking at the potential risks and safeguards involved with this fast rising activity. The authors discuss the psychological mechanisms that may contribute to excessive trading, such as the illusion of control, biased attributions, hindsight bias, and the hot-hand fallacy. In terms of psychological risk concerns, they also compare and contrast crypto trading, online sports betting, and day trading. The market's worldwide nature and constant 24-hour availability are also considered, as are potential defensive tactics such as finding out credible information sources and imposing restrictions on price monitoring. Overall, this report gives a thorough grasp of the psychological processes at work in crypto-currency trading, highlighting the need for additional research as well as potential measures for trading platform regulation (Zhao & Zhang, 2021) (Hussain, Hassan, Khan, & Khan, 2026).

The report examines how Bitcoin trading affects mental health, relationships, and finances. Motivations and the sustainability of bitcoin trading are factors in engagement. Trading in crypto-currencies can have both positive and negative consequences for participants. Participants use harm reduction measures to decrease mental distress caused by trading. Participants' expectations and intentions about bitcoin trading are heavily influenced by social settings, particularly celebrity and influencer endorsements. Participants warn against accepting the advice of influencers and emphasize the need to accurately represent advantages and hazards. Many individuals were introduced to crypto-currencies by acquaintances and were advised to trade as a means of making money. Some individuals were driven by financial necessity, whereas others were motivated by wealth dreams. Participants' initial expectations were impacted by crypto-currency marketing, particularly those promoting a glamorous lifestyle (Bui, 2022; Sonkurt & Altınöz, 2021).

Crypto-currencies are digital currencies that may be exchanged online without the intervention of a central administrator, making them appealing for high-risk trading patterns similar to gambling. Impulsivity, novelty seeking, and a fear of losing out are common personality traits among bitcoin traders. Crypto-currency trading has been linked to problem gambling, and it shares demographic and personality traits with high-risk stock trading and problem gambling. Intense crypto-currency trading has been related to gambling addiction, and some traders engage in pathological trading. The psychological impacts of bitcoin trading are mixed (Bin-Nashwan, Abdellatif Ismaiel, Tawfik, & Sadallah, 2026; Nurbarani & Soepriyanto, 2022).

In the short and long run, crypto market-related characteristics such as market beta, trading volume, and volatility are major influencers for all five crypto-currencies. The popularity of crypto-currencies also influences their price, but only in the long run. This suggests that market acknowledgment of the attractiveness of crypto-currencies takes time to emerge (Hussain & Durrani, 2026). Except for Bitcoin, which has a statistically significant estimate of -0.20 at a 10% significance level, the SP500 index has a weak positive long-run influence on Bit coin, Ethereum, and Lite coin. According to the ECM theory, error correction terms (ECT) in all models are statistically significant at the 1% level with a negative sign. Bitcoin recovered 23.68% of its previous period imbalance, whereas Ethereum, Dash, Lite coin, and Monero recovered 12.76%, 10.20%, 22.91%, and 14.27%, respectively. In the long term, the SP500 index has a slight positive significant coefficient in Bit coin, Ethereum, and Lite coin models, but this link vanishes in the short run, with the exception of Bitcoin, which predicts a negative estimate of -0.2020 at a 10% significance level. Except for Bitcoin, which predicts an estimate of the SP500 factor of -0.2020 at a 10% significance level, macroeconomic control variables are insignificant in all short-run models. This suggests that a rise in the SP500 index causes Bitcoin prices to fall in the short run. The time factor influences the impact of attractiveness on crypto-currencies, with Bitcoin being the only model that forecasts a significant coefficient of 0.14 at a 10% significance level. This implies that the market requires time to create and recognize attraction (Hussain, Ali, Hassan, & Khan, 2026; Hussain, Shah, Durrani, & Hassan, 2023).

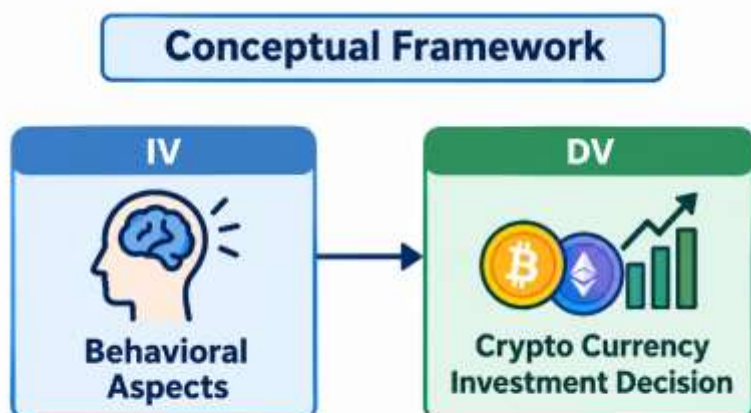
3. Research Methodology

This study employed a quantitative research approach to examine the impact of behavioral aspects on crypto-currency investment decisions. The study was causal in nature, as it aimed to determine whether different behavioral factors significantly influence individuals' decisions regarding crypto-currency investment. Primary data were collected directly from respondents through a structured questionnaire adapted from previously developed and established measures.

A non-probability convenience sampling technique was used to select respondents who were accessible and willing to participate in the study. Data were collected through physical questionnaires distributed to the selected respondents. After collection, the responses were coded and analyzed using the Statistical Package for the Social Sciences (SPSS).

Several statistical techniques were applied to analyze the data. Descriptive statistics were used to summarize the characteristics and responses of the participants. Reliability analysis was conducted to assess the internal consistency of the measurement scales. Correlation analysis was used to examine the relationships between behavioral factors and crypto-currency investment decisions, while regression analysis was performed to determine the extent to which behavioral aspects predict crypto-currency investment decisions. These analytical techniques provided a systematic basis for examining the proposed relationships among the study variables.

3.1. Conceptual Framework



4.0. Data Analysis and Results

4.1. Table No. 1 Reliability Analysis

Reliability Statistics	
Cronbach's Alpha	N of Items
.756	24

Interpretation: A reliability analysis was performed to assess the consistency of factors associated with investor attitudes, overconfidence, salience, overreaction, herding behavior, and investment decisions. Cronbach's Alpha was employed in this analysis to quantify the variables' internal consistency which is 0.756 and it shows that scale is valid for further process.

4.2. Table No. 2 Frequency Analysis

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	75	75.0	75.0	75.0
	Female	25	25.0	25.0	100.0
	Total	100	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	16-26	80	80.0	80.0	80.0
	26-35	4	4.0	4.0	84.0
	36-45	16	16.0	16.0	100.0
	Total	100	100.0	100.0	

Qualification

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Masters	24	24.0	24.0	24.0
	Bachelors	76	76.0	76.0	100.0
	Total	100	100.0	100.0	

Interpretation: The demographic characteristics of the respondents provide an overview of the sample used in the study. The results show that 75% of the respondents were male, while 25% were female. This indicates that male respondents constituted the majority of the sample, whereas female participation was comparatively lower.

In terms of age, the majority of respondents were relatively young. Specifically, 80% of the participants were between 16 and 26 years of age. A further 4% belonged to the 26–35 age group, while 16% were between 36 and 45 years. The findings therefore indicate that the sample was largely represented by younger respondents, with comparatively fewer participants in the middle-age categories.

Regarding educational qualification, 76% of respondents held a bachelor's degree, while 24% had a master's degree. This shows that the majority of participants had an undergraduate-level qualification, while nearly one-fourth had postgraduate education.

Overall, the demographic profile indicates that the study sample was predominantly male, young, and bachelor-qualified. These characteristics provide useful background information for understanding the respondents included in the analysis of behavioral aspects toward crypto-currency investment.

4.3. Table No. 3 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.725 ^a	.526	.501	.59016

Model Summary Interpretation: The model summary indicates a strong positive relationship between behavioral aspects and crypto-currency investment decisions, with an R value of 0.725. The R^2 value of 0.526 shows that the behavioral factors included in the model explain approximately 52.6% of the variation in crypto-currency investment decisions. The adjusted R^2 of 0.501 indicates that, after accounting for the predictors included in the model, approximately 50.1% of the variance in crypto-currency investment decisions is explained. The standard error of the estimate is 0.59016, indicating the average level of prediction error in the model. Overall, the results suggest that the model provides a substantial explanation of crypto-currency investment decisions based on the behavioral factors examined.

4.4. Table No. 4 Anova

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.348	5	7.270	20.872	.000 ^b
	Residual	32.739	94	.348		
	Total	69.087	99			

ANOVA Interpretation: The ANOVA results show that the regression model is statistically significant, with an F-value of 20.872 and a significance level of $p < .001$. This indicates that the behavioral factors, when considered together, have a statistically significant relationship with crypto-currency investment decisions. The regression model explains a significant portion of the variation in the dependent variable, as reflected by the regression sum of squares (36.348) compared with the residual sum of squares (32.739). Therefore, the overall regression model is suitable for examining the impact of the selected behavioral factors on crypto-currency investment decisions.

4.5. Table No. 5. Regression Analysis

Coefficient						
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	.683	.603		1.133	.260
	Investorsentiments	.285	.081	.272	3.511	.001
	Overconfidence	.474	.094	.451	5.044	.000
	SALIENCE	-.271	.104	-.202	-2.610	.011
	OVERREACTION	-.045	.120	-.031	-.374	.709
	HERDINGBEHAVIOR	.374	.109	.275	3.438	.001

Regression Interpretation: The coefficient results show the individual effects of the behavioral factors on crypto-currency investment decisions. Investor sentiment has a positive and statistically significant effect ($\beta = 0.272$, $p = .001$), indicating that higher investor sentiment is associated with higher crypto-currency investment decisions. Overconfidence also has a positive and significant effect ($\beta = 0.451$, $p < .001$), making it the strongest predictor among the variables based on the standardized coefficient.

Salience has a negative and statistically significant effect ($\beta = -0.202$, $p = .011$), suggesting that higher salience is associated with lower crypto-currency investment decisions. In contrast, overreaction has a negative but statistically insignificant effect ($\beta = -0.031$, $p = .709$), indicating that it does not significantly influence crypto-currency investment decisions in this model.

Herding behavior shows a positive and statistically significant effect ($\beta = 0.275$, $p = .001$), indicating that greater herding behavior is associated with higher crypto-currency investment decisions. Overall, investor sentiment, overconfidence, salience, and herding behavior significantly influence crypto-currency investment decisions, while overreaction does not show a significant effect.

4.6. Table No. 6. Correlation Analysis

Correlations				
		Investorsentiments	overconfidenc e	SALIENCE
Investor sentiments	Pearson Correlation	1	.045	-.370**
	Sig. (2-tailed)		.654	.000
	N	100	100	100
overconfidence	Pearson Correlation	.045	1	.090
	Sig. (2-tailed)	.654		.373
	N	100	100	100
SALIENCE	Pearson Correlation	-.370**	.090	1
	Sig. (2-tailed)	.000	.373	
	N	100	100	100
OVERREACTION	Pearson Correlation	.104	.509**	.107

	Sig. (2-tailed)	.304	.000	.290
	N	100	100	100
HERDINGBEHAVIOR	Pearson Correlation	.032	.459**	.029
	Sig. (2-tailed)	.755	.000	.774
	N	100	100	100
INVESTMENTDECISION	Pearson Correlation	.372**	.556**	-.257**
	Sig. (2-tailed)	.000	.000	.010
	N	100	100	100

Correlation Analysis Interpretation: The correlation results show the relationships between the behavioral factors and crypto-currency investment decisions among the 100 respondents. Investor sentiment has a positive and significant relationship with investment decisions ($r = .372$, $p < .001$), indicating that higher investor sentiment is associated with greater crypto-currency investment decisions. Similarly, overconfidence has a positive and significant relationship with investment decisions ($r = .556$, $p < .001$), representing the strongest correlation among the behavioral factors.

Salience has a negative and significant relationship with investment decisions ($r = -.257$, $p = .010$), suggesting that higher salience is associated with lower investment decisions. The correlations between overreaction and herding behavior with investment decisions are not shown in the provided table, so no conclusion about their bivariate relationships should be drawn from this output.

Among the independent variables, investor sentiment is negatively related to salience ($r = -.370$, $p < .001$), while overconfidence is positively related to overreaction ($r = .509$, $p < .001$) and herding behavior ($r = .459$, $p < .001$). Overall, the correlation results indicate meaningful relationships between several behavioral factors and crypto-currency investment decisions.

5.0. Conclusion

This study examined the role of behavioral factors in crypto-currency investment decisions, with particular attention to investor sentiment, overconfidence, salience, overreaction, and herding behavior. The findings show that behavioral factors play an important role in shaping crypto-currency investment decisions. Investor sentiment, overconfidence, and herding behavior were found to have significant positive effects, while salience had a significant negative effect. In contrast, overreaction did not have a statistically significant effect on investment decisions (Hussain, Hassan, Khan, & Khan, 2024). The findings highlight that crypto-currency investment decisions are not influenced only by financial considerations but are also shaped by investors' perceptions, emotions, and behavioral tendencies. The strong effect of overconfidence suggests that investors' beliefs about their own knowledge and decision-

making ability may influence their willingness to invest in crypto-currencies. Similarly, the significant role of investor sentiment and herding behavior indicates that market perceptions and the actions of other investors can also contribute to investment decisions (Ahmed, Rehman, & Hussain, 2024).

Overall, the study emphasizes the importance of informed decision-making, awareness of behavioral biases, and appropriate risk management in crypto-currency investment. The findings may be useful for investors, financial educators, and policymakers seeking to better understand investor behavior in the developing crypto-currency market. Further research using larger and more diverse samples, as well as additional behavioral and financial variables, could provide a broader understanding of crypto-currency investment behavior.

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