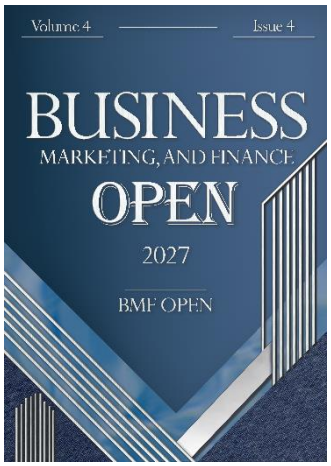
Investor Sentiment and Cryptocurrency Market Volatility: Evidence from High-Frequency Digital Asset Data

Mehdi Hosseiny Farzad [1,*]

[1] Graduate School of Management and Economics, Sharif University of Technology, Iran;

* Correspondence: mahdi_hosseinyfarzad@gsme.sharif.edu



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Abstract: This study aimed to examine the relationship between investor sentiment and cryptocurrency market volatility by integrating survey-based sentiment data from active cryptocurrency investors in Tehran with high-frequency digital asset market data. This quantitative explanatory-correlational study was conducted among 384 active cryptocurrency investors residing in Tehran who were selected through purposive sampling based on trading experience and direct involvement in digital asset investment. Investor sentiment was measured using a structured questionnaire assessing optimism, fear of loss, risk appetite, herding tendency, overreaction to market news, and speculative enthusiasm. High-frequency market data were collected at five-minute intervals for Bitcoin, Ethereum, Binance Coin, Solana, and Ripple over a 90-day observation period. Market variables included log returns, absolute returns, trading volume, bid-ask spread, and realized volatility. Data were analyzed using descriptive statistics, Pearson correlation, GARCH(1,1) volatility modeling, fixed-effects panel regression, and hierarchical regression analysis. Investor sentiment was positively and significantly correlated with realized volatility ($r = 0.46$, $p < 0.01$), absolute log return ($r = 0.38$, $p < 0.01$), trading volume ($r = 0.31$, $p < 0.01$), and bid-ask spread ($r = 0.22$, $p < 0.01$). The GARCH(1,1) model showed significant ARCH ($\beta = 0.184$, $p < 0.001$) and GARCH effects ($\beta = 0.741$, $p < 0.001$), confirming volatility clustering and persistence. Investor sentiment significantly increased conditional volatility ($\beta = 0.057$, $p < 0.001$). Fixed-effects regression showed that speculative enthusiasm, overreaction to market news, fear of loss, herding tendency, and optimism significantly predicted realized volatility. Hierarchical regression indicated that investor sentiment added 11% explanatory power beyond market indicators. The findings demonstrate that investor sentiment is a significant behavioral determinant of cryptocurrency market volatility. Sentiment-driven optimism, fear, herding, and news overreaction intensify short-term instability in digital asset markets beyond the effects of conventional market variables.

Keywords: Investor sentiment; cryptocurrency; market volatility; high-frequency data; behavioral finance; GARCH model.

1. Introduction

Cryptocurrency markets have developed from a marginal technological innovation into a complex global financial ecosystem characterized by continuous trading, extreme information sensitivity, cross-platform fragmentation, and rapid investor reaction. Unlike traditional equity and bond markets, digital asset markets operate twenty-four hours a day, seven days a week, and therefore produce a dense flow of high-frequency price, volume, liquidity, and order-related information. This continuous market structure creates a distinctive environment in which volatility is not merely a periodic response to scheduled macroeconomic or corporate announcements, but a permanent feature of market behavior shaped by liquidity conditions, investor attention, speculative expectations, social media signals,

and algorithmic trading activity. The cryptocurrency market is also distinguished by the dominance of retail investors, the absence of uniform valuation anchors, and the strong role of narratives, all of which make investor sentiment a potentially powerful determinant of price instability. Behavioral finance has therefore become central to explaining cryptocurrency dynamics because digital assets often respond sharply to fear, greed, herding, news intensity, and speculative enthusiasm rather than to fundamental cash-flow-based valuation models [1-3].

Volatility is one of the most important characteristics of cryptocurrency markets because it affects investment decisions, portfolio allocation, risk management, derivatives pricing, market efficiency, and regulatory assessment. In digital asset markets, volatility is frequently more persistent and abrupt than in mature asset classes, reflecting both structural and behavioral factors. Comparative evidence suggests that cryptocurrencies can exhibit volatility patterns that differ substantially from those of traditional financial assets, especially in terms of magnitude, clustering, tail behavior, and sensitivity to market sentiment [4]. Studies on Bitcoin and other major cryptocurrencies have shown that volatility clustering and leverage-type effects are central features of the market, meaning that large shocks are often followed by further instability and that negative and positive shocks may have asymmetric implications for subsequent volatility [5]. High volatility also increases the importance of methodological choices, because daily data may conceal intraday price pressure, abrupt liquidity shortages, and sentiment-driven micro-movements that are visible only at higher frequencies [6-8].

The emergence of high-frequency cryptocurrency data has opened new opportunities for examining how digital asset prices respond to market information and investor behavior in real time. High-frequency analysis is particularly appropriate in this field because cryptocurrency markets continuously incorporate new signals from exchanges, news platforms, social networks, derivatives markets, and decentralized trading environments. Prior studies have emphasized the value of intraday data for understanding Bitcoin dynamics, stablecoin behavior, cross-asset spillovers, price discovery, and short-term risk formation [9-11]. High-frequency approaches are also important for volatility measurement because intraday returns provide richer information about realized volatility, jump behavior, and tail risk than low-frequency observations. This is especially relevant in cryptocurrency markets, where sharp price movements may emerge and disappear within hours or even minutes. For this reason, recent research has increasingly applied realized volatility, realized-GARCH models, high-frequency risk estimation, and ultra-high-frequency tail-risk techniques to capture the temporal structure of digital asset instability [12-15].

Investor sentiment refers to the collective emotional, cognitive, and behavioral orientation of market participants toward an asset or market. In cryptocurrency markets, sentiment is particularly important because investors often face high uncertainty, limited intrinsic valuation standards, strong information asymmetry, and intense exposure to social media narratives. Sentiment may appear as optimism about future prices, fear of loss, speculative excitement, panic selling, herding behavior, or overreaction to news. Theoretical and empirical work has shown that sentiment can influence both returns and volatility by affecting trading intensity, liquidity demand, and the speed with which market participants respond to signals [2, 16]. The time-varying relationship between sentiment and cryptocurrency markets suggests that sentiment does not influence prices uniformly across all conditions; rather, its effect may strengthen during unstable periods, periods of investor attention, or episodes of extreme market uncertainty. In this context, sentiment is not simply a psychological background variable but a dynamic market force that interacts with volatility formation.

One of the most visible sentiment mechanisms in cryptocurrency markets is the fear-greed cycle. Periods of greed can increase speculative buying, leverage, trading volume, and momentum-chasing behavior, while periods of fear can increase panic selling, liquidity withdrawal, and abrupt price declines. Recent evidence has shown that investor

greed and fear have meaningful causal relationships with cryptocurrency returns, particularly for major assets such as Bitcoin and Ethereum [17]. The concept of sentiment regimes further suggests that extreme sentiment states may create adverse selection and instability because informed and uninformed traders interact under conditions of asymmetric information and rapid belief revision [18]. This is important because volatility may be especially high not only when sentiment is positive or negative, but when sentiment becomes extreme. Therefore, the study of cryptocurrency volatility requires attention to both the direction and intensity of investor sentiment.

Herding is another behavioral mechanism through which sentiment may increase cryptocurrency volatility. Herding occurs when investors follow the actions of others rather than relying on independent analysis, which can amplify price trends and increase market fragility. In cryptocurrency markets, herding may be intensified by online communities, influencer activity, exchange-level price movements, algorithmic signals, and fear of missing out. During turbulent periods such as the COVID-19 pandemic, herding intensity was shown to be connected with cryptocurrency volatility, indicating that collective investor behavior can contribute to market instability [19]. Intraday herding and attention dynamics also suggest that behavioral convergence can occur rapidly and repeatedly across the trading day, reinforcing the need for high-frequency analysis [20]. When a large number of investors respond similarly to price signals, rumors, or social media discussions, market depth may weaken and volatility may rise sharply.

Investor attention is closely related to sentiment but represents a distinct mechanism. Attention determines which information is noticed, processed, and translated into trading behavior. In cryptocurrency markets, attention can be a double-edged sword because it may increase liquidity by attracting market participation, but it may also increase volatility by intensifying reaction to signals and accelerating speculative trading [21]. Twitter-based sentiment and social media activity have been linked to Bitcoin returns and high-frequency volatility, showing that digital communication platforms can transmit investor mood into measurable market outcomes [16]. The role of attention is also evident in research on intraday reactions to Tether minting and burning events, where large stablecoin-related announcements and "whale alerts" were associated with asymmetric market responses and investor sentiment effects [22]. These findings suggest that cryptocurrency volatility cannot be fully understood without considering how investors interpret and react to attention-generating events.

News is another major driver of sentiment and volatility in digital asset markets. Cryptocurrency prices are highly sensitive to regulatory announcements, exchange failures, technological developments, adoption news, macroeconomic uncertainty, and social media narratives. However, the impact of news is not always linear or proportional to its informational content; instead, market reactions often depend on investor interpretation, emotional intensity, and the prevailing sentiment environment. Research evaluating the real impact of news on cryptocurrency volatility has emphasized that news-related effects may extend beyond simple information transmission and may be shaped by hype, behavioral overreaction, and market expectations [23]. This implies that news can become a volatility channel when investors respond collectively, rapidly, and emotionally, especially in high-frequency settings where reaction time is compressed.

Liquidity is also a crucial link between investor sentiment and volatility. Sentiment-driven trading may increase transaction volume, but this does not necessarily improve market quality. When optimistic or fearful investors trade aggressively, bid-ask spreads may widen, liquidity premiums may rise, and realized volatility may increase. Research on investor attention and market liquidity suggests that attention can support liquidity under some conditions while destabilizing the market under others [21]. Similarly, liquidity-adjusted return and volatility frameworks show that liquidity conditions are essential for understanding risk in portfolios of crypto assets [24].

When sentiment increases order imbalance or reduces the willingness of liquidity providers to absorb trades, volatility may rise even if trading volume is high. Therefore, liquidity indicators such as trading volume and bid-ask spread should be considered when modeling the relationship between investor sentiment and cryptocurrency volatility.

The market structure of cryptocurrency trading further complicates volatility formation. Unlike centralized traditional exchanges with standardized rules, cryptocurrency markets are fragmented across spot exchanges, futures markets, derivatives platforms, decentralized exchanges, and stablecoin pairs. Futures markets and derivatives can contribute to price discovery, hedging, speculation, and volatility transmission. Research on Bitcoin futures has shown that contract design, arbitrage, and market structure matter for understanding cryptocurrency price dynamics [25]. Studies on regular and Micro Bitcoin futures also highlight the time-varying nature of price discovery, suggesting that the relative informational role of spot and futures markets changes across market conditions [26]. More recent work has continued to question whether Bitcoin price discovery is led by spot or futures markets, indicating that the issue remains empirically complex [11]. These findings are relevant because sentiment-driven trading may be transmitted not only through spot prices but also through futures markets and related instruments.

Methodological advances have also expanded the ability to forecast and interpret cryptocurrency volatility. Machine learning, deep learning, hybrid volatility-sentiment models, and advanced econometric estimators are increasingly used to capture nonlinear and high-dimensional patterns in digital asset data [27, 28]. Forecasting studies suggest that sentiment can improve predictive models when combined with volatility and market variables, particularly because cryptocurrency markets are influenced by nontraditional information channels [27]. Deep learning applications in cryptocurrency research further demonstrate that complex models are being used to analyze price prediction, volatility estimation, trading strategies, and risk assessment [28]. However, despite these advances, traditional econometric approaches such as GARCH-family models remain valuable because they provide interpretable estimates of volatility persistence, shock effects, and the incremental contribution of explanatory variables such as sentiment.

Risk management in cryptocurrency markets requires special attention to realized volatility, tail risk, and extreme movements. Because digital asset returns often show fat tails and abrupt jumps, conventional risk models may underestimate losses during unstable periods. Conditional extreme value theory, semi-heavy-tail approaches, high-frequency value-at-risk models, and tail-risk estimation techniques have therefore become increasingly important in cryptocurrency research [13-15]. The pricing of cryptocurrency options also depends critically on volatility dynamics, including the volatility of volatility, which reflects uncertainty about future volatility itself [29]. These risk-management perspectives are relevant to investor sentiment because emotionally driven trading may increase not only average volatility but also the probability of extreme price changes. Thus, sentiment may have implications for both routine fluctuations and tail-risk exposure.

Cryptocurrency markets are also characterized by connectedness across assets and moments of distribution. Bitcoin, Ethereum, stablecoins, and alternative digital assets do not move independently; rather, they are linked through liquidity channels, investor portfolios, exchange structures, and shared sentiment regimes. Research on time-frequency co-movement and risk connectedness among cryptocurrencies has shown that higher-order moments and crisis periods can alter the degree of interdependence across assets [30, 31]. During transitions before and after COVID-19, the cryptocurrency market displayed changing investment opportunities and risk structures, indicating that market regimes influence volatility and investor behavior [32]. These findings reinforce the need to

examine cryptocurrency volatility in a framework that recognizes asset heterogeneity, time-varying relationships, and behavioral drivers.

The relevance of sentiment is not limited to cryptocurrency markets. Broader financial research has shown that investor mood, happiness, attention, and uncertainty can contribute to the predictability of realized volatility in other assets, such as gold and banking-sector equities [33, 34]. Similarly, economic policy uncertainty has been examined in relation to cryptocurrency markets as a potential risk-management avenue, suggesting that digital assets may respond to both financial-market sentiment and broader macroeconomic uncertainty [35]. These studies imply that investor sentiment should be understood within a wider behavioral-finance and uncertainty framework. However, cryptocurrency markets may represent a more intense case because they combine retail participation, continuous trading, social media influence, technological narratives, and weak valuation anchors.

Despite the growing literature on cryptocurrency sentiment, volatility, high-frequency trading, liquidity, and risk, important gaps remain. Many studies examine returns rather than volatility, use daily data rather than high-frequency observations, focus on market-level sentiment rather than investor-level sentiment, or investigate individual variables such as attention, news, fear, or herding without integrating them into a unified empirical design. Moreover, although high-frequency cryptocurrency data provide a powerful basis for capturing rapid volatility formation, fewer studies combine such data with survey-based investor sentiment indicators from an identifiable investor population. This integration is important because market data reveal what happens in prices and volumes, while investor sentiment data help explain why investors may respond to market signals in destabilizing ways. In markets such as Tehran, where cryptocurrency participation has grown alongside macroeconomic uncertainty, inflation concerns, exchange-rate sensitivity, and high interest in digital assets, examining investor sentiment can provide valuable insight into how behavioral factors interact with high-frequency market volatility.

The aim of this study was to examine the relationship between investor sentiment and cryptocurrency market volatility by integrating survey-based sentiment data from active cryptocurrency investors in Tehran with high-frequency digital asset market data.

2. Methodology

This study was conducted using a quantitative, applied, and explanatory-correlational design with a high-frequency financial data approach. The purpose of the study was to examine the relationship between investor sentiment and cryptocurrency market volatility by integrating survey-based sentiment data from individual investors with high-frequency digital asset market data. The statistical population consisted of active cryptocurrency investors residing in Tehran who had practical experience in buying, selling, or holding digital assets through domestic or international trading platforms. The participants were selected using purposive sampling because the study required respondents with direct exposure to cryptocurrency trading and sufficient familiarity with market fluctuations. The inclusion criteria were being at least 18 years old, residing in Tehran, having at least six months of cryptocurrency trading or investment experience, and conducting at least ten cryptocurrency transactions during the previous three months. Individuals who submitted incomplete questionnaires, reported no actual trading experience, or participated only as observers without any investment activity were excluded from the study. Initially, 431 questionnaires were collected; after screening for missing data, response inconsistency, and eligibility criteria, 384 valid questionnaires were retained for final analysis. Therefore, the final sample included 384 cryptocurrency investors from Tehran. In addition to the human sample, the market

component of the study consisted of high-frequency price and trading data for selected major cryptocurrencies, including Bitcoin, Ethereum, Binance Coin, Solana, and Ripple. The high-frequency dataset covered 5-minute trading intervals over a 90-day observation period, resulting in a structured panel of digital asset observations suitable for volatility modeling.

The Demographic and Digital Asset Trading Profile Form was used to collect background information about the participants and their cryptocurrency investment characteristics. This form included items related to age, gender, educational level, occupational status, monthly income, investment experience, average trading frequency, preferred digital assets, trading platform type, portfolio size, investment horizon, and exposure to cryptocurrency-related news and social media content. The purpose of this form was to describe the characteristics of the Tehran-based investor sample and to control for individual differences that could influence investor sentiment and trading behavior. The form was reviewed by specialists in financial management and behavioral finance to ensure content relevance, clarity, and consistency with the objectives of the study.

Investor sentiment was measured using a structured Investor Sentiment Questionnaire designed on the basis of behavioral finance constructs commonly used in studies of financial decision-making. The questionnaire assessed investors' emotional and cognitive orientations toward the cryptocurrency market, including optimism toward future price movements, perceived market confidence, fear of loss, risk appetite, herding tendency, overreaction to market news, and speculative enthusiasm. The instrument contained 28 items scored on a five-point Likert scale ranging from 1, indicating strongly disagree, to 5, indicating strongly agree. Higher scores represented stronger positive or speculative investor sentiment, while lower scores reflected cautious, pessimistic, or risk-averse sentiment. The total sentiment score was calculated by summing the item scores after reversing negatively worded items. The content validity of the questionnaire was evaluated by a panel of experts in finance, psychology, and research methodology, and its internal consistency was assessed using Cronbach's alpha. The reliability coefficient obtained for the total scale in the present study was acceptable, indicating that the instrument had adequate internal consistency for measuring investor sentiment among cryptocurrency investors.

High-frequency cryptocurrency market data were collected through structured digital asset market records extracted from recognized cryptocurrency trading data sources. The dataset included opening price, highest price, lowest price, closing price, trading volume, number of trades, and bid-ask spread indicators where available. Data were collected at 5-minute intervals for the selected cryptocurrencies in order to capture short-term market movements and intraday volatility dynamics. The use of high-frequency data allowed the study to examine market volatility more precisely than daily or weekly data, because cryptocurrency markets operate continuously and are highly sensitive to investor reactions, news, liquidity changes, and speculative activity. Before analysis, all timestamps were standardized, duplicate observations were removed, missing intervals were checked, and abnormal price records caused by data transmission errors were excluded. Volatility was operationalized using return-based indicators derived from logarithmic price changes, and realized volatility was calculated from high-frequency intraday returns.

A sentiment exposure index was also constructed to connect the survey-based investor sentiment scores with market-level volatility indicators. For this purpose, the individual sentiment scores were aggregated and standardized to represent the dominant sentiment tendency of the investor sample during the study period. The standardized sentiment index was then matched with the high-frequency market data according to the observation period. This procedure made it possible to examine whether stronger positive sentiment, fear-based sentiment, or speculative enthusiasm was associated with higher volatility in cryptocurrency prices. The integration of investor-

level and market-level data provided a stronger empirical basis for analyzing the behavioral dimension of cryptocurrency volatility.

Data analysis was performed in several stages. First, the completed questionnaires were screened for missing values, outliers, and response inconsistencies. Descriptive statistics, including frequency, percentage, mean, standard deviation, minimum, and maximum values, were used to summarize the demographic characteristics of the participants, their trading profiles, investor sentiment scores, and the main characteristics of the cryptocurrency market variables. The normality of survey-based variables was examined using skewness, kurtosis, and the Kolmogorov–Smirnov test, while the stationarity of high-frequency return series was evaluated using time-series diagnostic procedures. Before estimating the main models, cryptocurrency prices were transformed into logarithmic returns in order to obtain a more appropriate measure for financial volatility analysis.

In the inferential stage, correlation analysis was used to examine the preliminary relationships between investor sentiment, trading volume, return fluctuations, and realized volatility. To model cryptocurrency volatility, high-frequency return data were analyzed using volatility models appropriate for financial time series. ARCH and GARCH-type models were estimated to capture volatility clustering, persistence, and short-term market instability in digital asset prices. The investor sentiment index was included as an explanatory variable in the volatility equations to determine whether changes in sentiment contributed significantly to cryptocurrency market volatility. In addition, multiple regression analysis was used to assess the predictive role of investor sentiment after controlling for trading volume, asset type, and market liquidity indicators. For panel-based estimations, cryptocurrency-specific effects were considered in order to account for differences across digital assets.

Model adequacy was evaluated through diagnostic tests, including residual autocorrelation, heteroscedasticity checks, and goodness-of-fit indicators. The level of statistical significance was set at 0.05 for all inferential analyses. The results were interpreted based on the size, direction, and significance of the estimated coefficients. Positive and significant coefficients for investor sentiment were considered evidence that stronger speculative or optimistic sentiment was associated with increased cryptocurrency market volatility, whereas negative coefficients indicated a stabilizing or risk-reducing association. All statistical analyses were conducted using specialized statistical and econometric software suitable for survey analysis and high-frequency financial time-series modeling.

3. Findings and Results

The final analysis was conducted on data obtained from 384 active cryptocurrency investors residing in Tehran and a high-frequency digital asset dataset consisting of 129,600 five-minute observations across five major cryptocurrencies during the 90-day observation period. The demographic results showed that the mean age of participants was 31.84 years with a standard deviation of 7.26, and the age range was from 19 to 55 years. Of the participants, 236 individuals were male, representing 61.46 percent of the sample, and 148 individuals were female, representing 38.54 percent. In terms of educational level, 38 participants had a diploma or lower academic qualification, 211 had an associate or bachelor's degree, 103 had a master's degree, and 32 had a doctoral degree. Regarding cryptocurrency investment experience, 76 participants had between 6 and 12 months of trading experience, 167 had between 1 and 3 years of experience, and 141 had more than 3 years of experience in the cryptocurrency market. With respect to trading frequency, 121 participants reported daily trading activity, 147 reported trading several times per week, and 116 reported weekly or monthly trading activity. Bitcoin and Ethereum were the most frequently traded assets among participants, followed by Binance Coin, Solana, and

Ripple. Overall, the demographic and trading profile of the sample indicated that the participants had sufficient market exposure and practical experience to provide meaningful responses regarding investor sentiment and behavioral reactions to cryptocurrency market fluctuations.

Table 1. Descriptive Statistics of Investor Sentiment and Cryptocurrency Market Variables

Variable	Observation Level	N	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
Total investor sentiment	Individual investor	384	3.48	0.62	1.91	4.86	-0.21	2.74
Optimism toward future prices	Individual investor	384	3.63	0.71	1.60	5.00	-0.34	2.68
Fear of loss	Individual investor	384	3.28	0.78	1.20	5.00	0.18	2.59
Risk appetite	Individual investor	384	3.41	0.69	1.40	5.00	-0.12	2.81
Herding tendency	Individual investor	384	3.52	0.74	1.30	5.00	-0.27	2.66
Overreaction to market news	Individual investor	384	3.36	0.73	1.20	5.00	0.09	2.72
Speculative enthusiasm	Individual investor	384	3.58	0.76	1.30	5.00	-0.31	2.63
Five-minute log return	Asset-interval	129,600	0.00019	0.00642	-0.0718	0.0835	0.46	7.91
Absolute log return	Asset-interval	129,600	0.00487	0.00419	0.0000	0.0835	2.84	14.36
Trading volume, log-transformed	Asset-interval	129,600	14.87	1.09	11.42	18.36	0.31	3.08
Bid-ask spread percentage	Asset-interval	129,600	0.083	0.044	0.012	0.318	1.17	4.89
Realized volatility	Asset-day	450	0.392	0.211	0.071	1.184	1.09	4.21

The descriptive findings presented in Table 1 indicate that the mean total investor sentiment score was 3.48 out of 5, suggesting that the Tehran-based cryptocurrency investors generally reported a moderately positive and speculative orientation toward the digital asset market. Among the sentiment dimensions, optimism toward future prices had a relatively high mean score of 3.63, while speculative enthusiasm also showed a high mean value of 3.58. These results indicate that participants tended to expect future price growth and were emotionally engaged with short-term market opportunities. The mean score of herding tendency was 3.52, showing that a considerable proportion of investors were influenced by the behavior of other market participants, social media discussions, and perceived collective market movement. Fear of loss had a mean of 3.28, indicating that although the investors showed positive market expectations, they were also sensitive to potential losses and sudden price declines. The high-frequency market variables showed typical characteristics of cryptocurrency data. The five-minute log return had a small positive mean but a relatively high standard deviation, confirming the unstable and rapidly changing nature of digital asset prices. The kurtosis of five-minute returns was 7.91, indicating a fat-tailed distribution and the presence of extreme return observations. The absolute return and realized volatility indicators also showed positive skewness, suggesting that large volatility spikes occurred during specific market intervals. These findings support the appropriateness of applying volatility models to examine the dynamic relationship between investor sentiment and cryptocurrency market instability.

Table 2. Pearson Correlation Matrix among Investor Sentiment and Market Volatility Indicators

Variable	1	2	3	4	5	6
1. Investor sentiment index	1.00					
2. Realized volatility	0.46**	1.00				
3. Absolute log return	0.38**	0.74**	1.00			
4. Trading volume	0.31**	0.42**	0.39**	1.00		
5. Bid-ask spread	0.22**	0.35**	0.29**	0.18**	1.00	
6. Market return	0.19**	0.08	0.11*	0.26**	-0.07	1.00

Note. Correlations were calculated at the asset-day level after aggregation of high-frequency observations. *p < 0.05. **p < 0.01.

The correlation results in Table 2 show that the investor sentiment index had a positive and statistically significant relationship with realized volatility, $r = 0.46$, $p < 0.01$. This finding indicates that stronger investor

sentiment was associated with higher cryptocurrency market volatility. Investor sentiment was also positively correlated with absolute log return, $r = 0.38$, $p < 0.01$, suggesting that stronger sentiment was related not only to general price movement but also to the magnitude of market fluctuations. The positive correlation between investor sentiment and trading volume, $r = 0.31$, $p < 0.01$, indicates that sentiment was associated with more active market participation and higher transaction intensity. In addition, investor sentiment had a smaller but significant positive relationship with bid-ask spread, $r = 0.22$, $p < 0.01$, suggesting that periods of stronger sentiment were also accompanied by lower market stability and greater liquidity pressure. Realized volatility showed a strong positive correlation with absolute log return, $r = 0.74$, $p < 0.01$, confirming that the realized volatility measure was consistent with the magnitude of short-term return fluctuations. The correlation between realized volatility and trading volume was also positive and significant, $r = 0.42$, $p < 0.01$, indicating that periods of higher trading activity were associated with stronger volatility. Overall, the correlation findings provide preliminary evidence that sentiment, transaction intensity, and liquidity conditions were meaningfully connected with cryptocurrency volatility.

Table 3. GARCH(1,1) Model Estimating the Effect of Investor Sentiment on High-Frequency Cryptocurrency Volatility

Model Component	Variable	Coefficient	Standard Error	z-value	p-value
Mean equation	Constant	0.00018	0.00009	2.04	0.041
Mean equation	Investor sentiment index	0.00031	0.00012	2.66	0.008
Mean equation	Trading volume	0.00007	0.00003	2.39	0.017
Variance equation	Constant volatility term	0.000004	0.000001	5.38	<0.001
Variance equation	ARCH effect	0.184	0.015	12.46	<0.001
Variance equation	GARCH effect	0.741	0.016	48.37	<0.001
Variance equation	Investor sentiment index	0.057	0.009	6.12	<0.001
Variance equation	Fear of loss	0.032	0.008	4.19	<0.001
Variance equation	Herding tendency	0.038	0.009	4.53	<0.001
Variance equation	Overreaction to market news	0.041	0.008	5.06	<0.001
Variance equation	Speculative enthusiasm	0.046	0.008	5.73	<0.001
Variance equation	Bid-ask spread	0.028	0.006	4.71	<0.001
Variance equation	Trading volume	0.021	0.005	3.86	<0.001

Note. Dependent variable: five-minute cryptocurrency log return. Number of asset-interval observations = 129,600. Log likelihood = 382,451.72; AIC = -5.901; BIC = -5.898. ARCH + GARCH persistence coefficient = 0.925.

The GARCH(1,1) findings in Table 3 show that the cryptocurrency return series exhibited strong volatility clustering. The ARCH coefficient was positive and significant, $\beta = 0.184$, $p < 0.001$, indicating that recent market shocks had a significant effect on current volatility. The GARCH coefficient was also positive and highly significant, $\beta = 0.741$, $p < 0.001$, showing that past volatility had a strong persistence effect on current volatility. The sum of the ARCH and GARCH coefficients was 0.925, which indicates that volatility in the cryptocurrency market was highly persistent but still mean-reverting. More importantly, the investor sentiment index had a positive and significant effect in the variance equation, $\beta = 0.057$, $p < 0.001$. This result demonstrates that stronger investor sentiment significantly increased conditional volatility in high-frequency cryptocurrency returns. Among the sentiment dimensions, speculative enthusiasm, overreaction to market news, herding tendency, and fear of loss all had positive and significant coefficients, meaning that both positive and fear-based emotional reactions contributed to volatility formation. Speculative enthusiasm had one of the strongest sentiment-related effects, $\beta = 0.046$, $p < 0.001$, suggesting that emotionally driven expectations of rapid price gains intensified short-term market instability. Overreaction to market news was also a significant predictor of volatility, $\beta = 0.041$, $p < 0.001$, indicating that rapid

behavioral responses to news and online information increased price fluctuations. In addition, bid-ask spread and trading volume were significant predictors in the variance equation, showing that volatility increased under conditions of higher trading intensity and weaker liquidity. Overall, the GARCH model confirmed that investor sentiment was not merely associated with cryptocurrency volatility but contributed significantly to the conditional volatility process in high-frequency digital asset markets.

Table 4. Fixed-Effects Panel Regression Predicting Realized Cryptocurrency Volatility

Predictor	B	Standard Error	Standardized Beta	t-value	p-value
Constant	0.126	0.031	—	4.06	<0.001
Optimism toward future prices	0.028	0.011	0.14	2.62	0.009
Fear of loss	0.035	0.011	0.19	3.16	0.002
Risk appetite	0.019	0.010	0.10	1.91	0.057
Herding tendency	0.031	0.011	0.16	2.77	0.006
Overreaction to market news	0.044	0.010	0.23	4.31	<0.001
Speculative enthusiasm	0.052	0.011	0.27	4.89	<0.001
Trading volume	0.039	0.008	0.25	4.78	<0.001
Bid-ask spread	0.025	0.010	0.11	2.37	0.018
Absolute market return	0.289	0.031	0.41	9.32	<0.001

Note. Dependent variable: realized volatility. Number of asset-day observations = 450. Asset fixed effects were included in the model. $F = 46.28$, $p < 0.001$; $R^2 = 0.57$; adjusted $R^2 = 0.55$; Durbin-Watson = 1.96.

The fixed-effects panel regression results presented in Table 4 indicate that the model explained a substantial proportion of variation in realized cryptocurrency volatility. The overall model was statistically significant, $F = 46.28$, $p < 0.001$, and the adjusted R^2 value of 0.55 showed that approximately 55 percent of the variance in realized volatility was explained by investor sentiment dimensions, market activity, liquidity conditions, and absolute price movement after controlling for asset-specific differences. Among the sentiment dimensions, speculative enthusiasm was a strong and significant predictor of realized volatility, $B = 0.052$, $p < 0.001$, indicating that stronger speculative expectations were associated with higher volatility in the cryptocurrency market. Overreaction to market news was also a significant predictor, $B = 0.044$, $p < 0.001$, showing that investors' rapid emotional and cognitive responses to market-related information contributed to volatility. Fear of loss significantly predicted realized volatility, $B = 0.035$, $p = 0.002$, suggesting that downside sensitivity and fear-based reactions intensified market instability. Herding tendency was another significant predictor, $B = 0.031$, $p = 0.006$, meaning that investors who followed the behavior of other market participants were associated with stronger volatility patterns. Optimism toward future prices also had a significant positive effect, $B = 0.028$, $p = 0.009$, although its standardized effect was smaller than those of speculative enthusiasm and overreaction to news. Risk appetite approached statistical significance, $B = 0.019$, $p = 0.057$, but did not reach the conventional 0.05 threshold. Among the market variables, absolute market return had the strongest standardized effect, $\beta = 0.41$, $p < 0.001$, confirming that larger price movements were directly associated with higher realized volatility. Trading volume and bid-ask spread also significantly predicted realized volatility, indicating that market activity and liquidity conditions were important components of volatility formation. These results show that behavioral sentiment variables remained significant even after controlling for objective market indicators, supporting the central assumption that investor sentiment plays an independent role in cryptocurrency market volatility.

Table 5. Hierarchical Regression Analysis of the Incremental Predictive Power of Investor Sentiment

Model	Predictors Entered	R	R^2	Adjusted R^2	ΔR^2	F-change	p-value
Model 1	Trading volume, bid-ask spread, absolute market return	0.64	0.41	0.40	—	102.34	<0.001

Model 2	Model 1 + total investor sentiment index	0.72	0.52	0.51	0.11	48.67	<0.001
Model 3	Model 2 + sentiment dimensions	0.76	0.58	0.56	0.06	17.84	<0.001

The hierarchical regression results in Table 5 further confirm the incremental explanatory value of investor sentiment in predicting cryptocurrency market volatility. In the first model, objective market indicators, including trading volume, bid-ask spread, and absolute market return, explained 41 percent of the variance in realized volatility. This finding shows that market activity, liquidity pressure, and the magnitude of price movements were important baseline predictors of volatility. After the total investor sentiment index was entered in the second model, the explained variance increased from 41 percent to 52 percent. The change in R^2 was 0.11, and the F-change was statistically significant, F-change = 48.67, $p < 0.001$. This result indicates that investor sentiment added 11 percent unique explanatory power beyond the contribution of objective market variables. In the third model, the individual sentiment dimensions were added, increasing the explained variance from 52 percent to 58 percent. The additional change in R^2 was 0.06, and this increase was also statistically significant, F-change = 17.84, $p < 0.001$. Therefore, the hierarchical analysis demonstrated that sentiment was not only a general psychological construct associated with volatility but also a multidimensional behavioral mechanism through which optimism, fear of loss, herding behavior, news overreaction, and speculative enthusiasm contributed to market instability. The strongest improvement occurred when total sentiment was added to the baseline market model, confirming that investor sentiment provided meaningful predictive information beyond conventional market indicators.

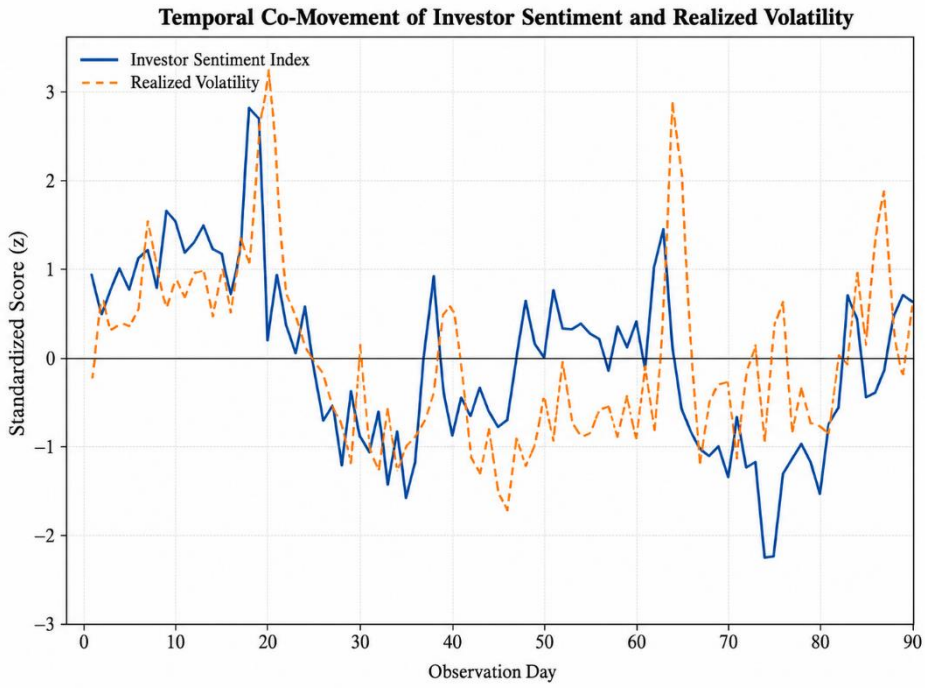

Figure 1. Temporal Co-Movement of Standardized Investor Sentiment and Realized Cryptocurrency Market Volatility during the 90-Day Observation Period

The pattern shown in Figure 1 indicated a visible co-movement between standardized investor sentiment and realized cryptocurrency market volatility over the 90-day observation period. Periods characterized by stronger positive sentiment, speculative enthusiasm, and increased attention to market news were generally followed by higher volatility levels. The most pronounced volatility spikes occurred during intervals in which the sentiment index moved sharply upward, suggesting that optimistic and speculative market reactions intensified short-term

price fluctuations. At the same time, some volatility increases were observed during periods of declining sentiment, indicating that fear-based reactions and uncertainty also contributed to market instability. This pattern is consistent with the statistical findings from the correlation, GARCH, panel regression, and hierarchical regression analyses. Together, the visual and statistical evidence suggests that cryptocurrency volatility was not solely the outcome of mechanical market factors but was also shaped by behavioral responses among investors. The figure therefore supports the conclusion that investor sentiment acted as a dynamic behavioral force in the formation and persistence of high-frequency cryptocurrency market volatility.

4. Discussion and Conclusion

The present study examined the relationship between investor sentiment and cryptocurrency market volatility by integrating survey-based sentiment data from 384 active cryptocurrency investors in Tehran with high-frequency digital asset data collected at five-minute intervals across five major cryptocurrencies. The findings showed that the participants generally reported a moderately positive and speculative sentiment toward the cryptocurrency market. Among the sentiment dimensions, optimism toward future prices, speculative enthusiasm, and herding tendency obtained relatively higher mean scores, indicating that investors were not merely passive holders of digital assets but were behaviorally engaged with expectations of future price increases, short-term opportunities, and collective market signals. This pattern is consistent with behavioral finance perspectives on cryptocurrency markets, which argue that digital asset valuation is strongly influenced by psychological expectations, social influence, and speculative narratives rather than only by conventional fundamental indicators [1, 3]. The descriptive market findings also confirmed the unstable structure of cryptocurrency returns, as five-minute log returns displayed high dispersion and fat-tailed behavior. This result supports previous evidence showing that cryptocurrency markets are characterized by volatility clustering, extreme movements, and distributional irregularities that differentiate them from more mature financial markets [4, 5, 36].

The correlation analysis showed that the investor sentiment index was positively and significantly associated with realized volatility, absolute log returns, trading volume, and bid-ask spread. This means that stronger sentiment was related not only to price movement but also to the magnitude of fluctuations, transaction intensity, and liquidity pressure. This finding supports the argument that investor sentiment functions as a behavioral volatility channel in cryptocurrency markets. When investors become more optimistic, fearful, speculative, or reactive to market signals, their trading behavior may increase order imbalance, shorten decision horizons, and intensify price instability. This interpretation is aligned with wavelet-based evidence showing a time-varying nexus between investor sentiment and cryptocurrency markets [2]. It is also consistent with studies showing that Twitter-based financial sentiment can predict Bitcoin returns and high-frequency volatility [16], and that investor attention can act as a double-edged sword by improving liquidity under some conditions while increasing instability under others [21]. The positive association between sentiment and trading volume in the present study further confirms that sentiment is expressed through market participation, not merely through stated attitudes.

The GARCH results provided stronger evidence for the volatility-generating role of sentiment. The significant ARCH and GARCH coefficients indicated that cryptocurrency volatility was highly persistent and that recent shocks and past volatility strongly affected current volatility. This finding is consistent with previous studies reporting volatility clustering and persistent intraday instability in cryptocurrency markets [6-9]. More importantly, the investor sentiment index had a positive and significant effect in the variance equation, indicating that sentiment contributed directly to conditional volatility. This result supports studies that emphasize the behavioral nature of

cryptocurrency volatility, particularly the role of fear, greed, investor overreaction, and speculative expectations [17, 18]. The significance of speculative enthusiasm in the volatility equation suggests that investors' expectations of rapid gains can intensify short-term market movements, especially in markets where narratives and momentum are powerful drivers of decision-making. This is also compatible with evidence that machine learning and hybrid volatility-sentiment models improve cryptocurrency forecasting when they include sentiment-related information [27, 28].

Among the sentiment dimensions, overreaction to market news was one of the most important predictors of volatility. This finding indicates that cryptocurrency investors may respond quickly and emotionally to news, rumors, regulatory announcements, exchange-related events, and social media narratives. Such overreaction can transform information into excessive price movement, particularly in high-frequency settings where trading decisions occur rapidly. This result aligns with studies showing that news can influence cryptocurrency volatility beyond its objective informational value, especially when market participants interpret it through hype, fear, or exaggerated expectations [23]. It also corresponds with findings on the asymmetric intraday Bitcoin response to Tether minting and burning events and whale alerts, where investor sentiment and social media attention played important roles in short-term market reactions [22]. Therefore, the present study supports the view that cryptocurrency markets are not merely information-efficient systems but sentiment-sensitive environments in which news effects are filtered through behavioral interpretation.

The significant effect of herding tendency on realized volatility and conditional volatility is another important finding. Herding indicates that investors follow the perceived behavior of others instead of relying solely on their own independent analysis. In cryptocurrency markets, herding may occur through social media communities, influencer recommendations, price momentum, exchange leaderboards, and fear of missing out. The present findings suggest that herding contributes to volatility by synchronizing investor behavior and increasing the probability of collective buying or selling. This interpretation is supported by prior evidence showing that herding intensity is related to cryptocurrency volatility, particularly during unstable periods such as the COVID-19 crisis [19]. It is also consistent with research on intraday herding and attention, which suggests that behavioral convergence may occur across the trading day and affect price variation at short intervals [20]. In this sense, herding should be understood not simply as an irrational bias but as a market-level coordination mechanism that can amplify short-term volatility.

Fear of loss also significantly predicted volatility, showing that negative sentiment is as important as positive speculative enthusiasm in explaining market instability. Cryptocurrency investors often operate in a highly uncertain environment, where rapid losses, liquidation risk, leverage, and sudden market reversals are common. When fear increases, investors may sell quickly, reduce exposure, or react defensively to negative signals, thereby increasing volatility. This finding is consistent with evidence that greed and fear have meaningful causal relationships with Bitcoin and Ethereum returns [17]. It also supports the broader idea that cryptocurrency markets may become unstable under extreme sentiment regimes because emotional intensity increases adverse selection and accelerates belief revisions [18]. The simultaneous significance of fear of loss and speculative enthusiasm in the present study shows that volatility is not produced by only one emotional direction. Rather, both optimism-driven buying and fear-driven selling can destabilize the market when they become intense and collectively expressed.

The fixed-effects panel regression confirmed that sentiment variables remained significant predictors of realized volatility even after controlling for trading volume, bid-ask spread, absolute market return, and asset-specific effects. This result is important because it shows that sentiment had explanatory power beyond objective market

conditions. Absolute market return had the strongest standardized effect, which is expected because large price movements are mechanically linked with realized volatility. However, speculative enthusiasm, overreaction to news, fear of loss, herding tendency, and optimism all retained significant effects. These findings support the argument that high-frequency volatility in cryptocurrency markets results from an interaction between behavioral and structural factors. The importance of bid-ask spread and trading volume is aligned with liquidity-based research showing that liquidity conditions, liquidity-adjusted returns, and liquidity premiums are central to crypto-asset risk [24]. The findings also correspond with research on cross-asset spillovers and high-frequency price transmission, which shows that digital assets are embedded in rapidly moving liquidity and information networks [10].

The hierarchical regression analysis further showed that investor sentiment added substantial incremental explanatory power after accounting for conventional market variables. Market indicators explained a considerable share of volatility, but adding the total sentiment index substantially improved the model, and adding the individual sentiment dimensions further increased explanatory power. This confirms that sentiment is not a redundant proxy for volume or price movement; rather, it captures behavioral information that is not fully represented in standard market indicators. This result is compatible with studies emphasizing that high-frequency volatility models can be improved by incorporating external explanatory variables, sentiment proxies, or mixed-frequency information [12]. It also supports the growing use of advanced forecasting and hybrid models in cryptocurrency research, where behavioral data, volatility data, and machine learning techniques are combined to improve predictive accuracy [27, 28]. Therefore, the findings suggest that investor sentiment should be incorporated into empirical models of cryptocurrency volatility, especially when the goal is to understand short-term market instability.

The present findings also have implications for risk management and derivatives pricing. Since investor sentiment was associated with realized and conditional volatility, sentiment shifts may influence not only spot market risk but also futures, options, and other crypto-derivative markets. Prior research has shown that Bitcoin futures, Micro Bitcoin futures, and spot-futures price discovery relationships are dynamic and sensitive to market structure [11, 25, 26]. If sentiment intensifies spot-market volatility, it may also affect futures pricing, arbitrage conditions, and hedging effectiveness. Similarly, cryptocurrency options pricing depends on volatility dynamics and volatility of volatility, indicating that sentiment-driven instability may have implications for derivative valuation [29]. From a risk-management perspective, the fat-tailed and high-frequency nature of cryptocurrency volatility requires models that can capture extreme movements, jumps, and tail risk [13-15]. The present study contributes to this perspective by showing that sentiment may be one of the behavioral forces behind such volatility and tail-risk exposure.

The findings are also consistent with the literature on connectedness and regime-dependent behavior in cryptocurrency markets. Cryptocurrency assets are not isolated; they are linked through shared investor sentiment, liquidity channels, exchange mechanisms, and portfolio-level risk transmission. Prior studies have shown that time-frequency co-movement, higher-moment connectedness, and risk connectedness are important features of cryptocurrency markets [30, 31]. The present study's use of multiple digital assets and asset-specific controls supports the view that sentiment-driven volatility should be examined across the market rather than only within a single asset. In addition, the relationship between sentiment and volatility may vary across crisis periods, market regimes, and broader uncertainty conditions. Evidence from the transition before and after COVID-19 and from research on economic policy uncertainty suggests that cryptocurrency markets are sensitive to changing macro-

financial environments [32, 35]. The connection between attention and price variation during banking-sector stress also indicates that investor attention and market instability can intensify during episodes of financial uncertainty beyond the cryptocurrency market itself [34]. These findings reinforce the interpretation that sentiment is most influential when uncertainty, attention, and speculative pressure are simultaneously elevated.

Overall, the results of this study support the central assumption that investor sentiment plays a significant role in cryptocurrency market volatility. The findings showed that sentiment was positively related to realized volatility, significantly affected conditional volatility in the GARCH model, remained significant in fixed-effects panel regression, and added incremental predictive power beyond conventional market variables. These results are consistent with the broader behavioral-finance literature showing that emotions, attention, herding, and speculative beliefs influence digital asset dynamics [1, 2, 16]. They also extend the high-frequency cryptocurrency literature by showing that survey-based investor sentiment can be meaningfully integrated with intraday market data to explain volatility formation. Therefore, cryptocurrency volatility should be understood as the product of both market microstructure and investor psychology. Price instability in digital asset markets is not only a technical outcome of liquidity, volume, or past shocks, but also a behavioral outcome of how investors interpret uncertainty, react to news, imitate others, and express fear or enthusiasm through trading activity.

This study had several limitations that should be considered when interpreting the findings. First, the investor sample was limited to active cryptocurrency investors residing in Tehran, which may restrict the generalizability of the results to investors in other cities, countries, or regulatory environments. Second, investor sentiment was measured through self-report questionnaires, and responses may have been affected by social desirability, recall bias, or temporary market conditions at the time of data collection. Third, although the study used high-frequency market data, the observation period was limited to 90 days, and longer periods may capture additional market regimes, crisis episodes, or structural shifts. Fourth, the analysis focused on selected major cryptocurrencies, and the volatility behavior of smaller tokens, meme coins, decentralized finance assets, or low-liquidity assets may differ substantially. Finally, while the models identified statistically significant associations and predictive effects, causal interpretation should be made cautiously because cryptocurrency markets are influenced by multiple simultaneous behavioral, technological, macroeconomic, and regulatory factors.

Future studies are recommended to extend this research by using larger and more diverse samples of cryptocurrency investors across different geographic, economic, and regulatory contexts. Longitudinal designs could be used to measure investor sentiment repeatedly across bullish, bearish, and crisis market regimes in order to determine whether the sentiment-volatility relationship changes over time. Future research may also combine self-report sentiment data with real-time digital traces such as social media sentiment, search engine attention, exchange order-book information, and blockchain transaction data. In addition, future studies could compare different classes of digital assets, including stablecoins, governance tokens, decentralized finance tokens, and low-capitalization cryptocurrencies, to determine whether investor sentiment affects volatility differently across asset types. More advanced models such as nonlinear GARCH specifications, regime-switching models, machine learning algorithms, and causal inference frameworks may also provide a deeper understanding of how sentiment shocks are transmitted into volatility.

The findings of this study suggest that investors, analysts, exchange operators, and risk managers should treat investor sentiment as a practical market indicator rather than as a secondary psychological factor. Cryptocurrency investors should be trained to recognize how optimism, fear of loss, herding behavior, and overreaction to news can increase exposure to volatility and lead to impulsive trading decisions. Portfolio managers and financial

analysts can improve volatility monitoring by incorporating sentiment indicators alongside price, volume, liquidity, and return-based measures. Trading platforms may also benefit from developing investor education tools, warning systems, and behavioral risk dashboards that alert users when sentiment-driven market instability is likely to increase. Regulators and policymakers should also consider the role of sentiment amplification through social media, influencer activity, and rapid information diffusion when designing investor-protection frameworks for digital asset markets.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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