Impact of Market Sentiment on Gen Z Investment Choices

Dr. Deependra Kumar Sinha[1], Nidhi Arya[1], Ekta Arya[1], Fabian A. Tete[1], Aryan Kumar[2], Ujjwal Tirkey[2]

[1]Department of Vocational and Management Studies, St. Xavier's College, Ranchi

[2]Department of Financial Management Operation, St. Xavier's College, Ranchi

DOI: https://doi.org/10.51244/IJRSI.2026.1309000298

Received: 08 October 2026; Accepted: 13 October 2026; Published: 26 October 2026

ABSTRACT

This study examines how market sentiment, social-media exposure, trading-platform features, and artificial-intelligence tools relate to the investment choices of Generation Z. A structured online questionnaire produced 92 raw records between 20 August and 2 September 2026. Six unmistakable repeat submissions - identical respondent name and answer profile submitted within a short interval - were removed, leaving 86 cases. Descriptive statistics, Cronbach's alpha, Spearman correlation, Welch's t test, multiple ordinary least-squares regression with HC3 robust standard errors, binary logistic regression, one-way analysis of variance, Kruskal-Wallis testing, and a chi-square test with 20,000-label Monte Carlo calibration were applied. Agreement was high for fractional-share-enabled speculation (90.7%), economic-news-driven risk taking (86.0%), FOMO purchases near market peaks (83.7%), and notification-triggered trading without detailed research (84.9%). Nevertheless, the four proposed composite measures had weak internal consistency (alpha = 0.011 to 0.240; overall 12-item alpha = 0.400), so composite findings are interpreted as exploratory. Social sentiment susceptibility showed a small, non-significant association with digital trading impulsivity (Spearman rho = 0.157, p = 0.149); the adjusted regression was also non-significant (B = 0.167, HC3 p = 0.231; R-squared = 0.062). Crypto holders reported higher sentiment susceptibility than non-holders (M = 3.104 versus 2.899; Welch t = 2.032, p = 0.047, Hedges g = 0.429), but the corresponding logistic estimate was imprecise (odds ratio = 2.60, 95% CI [0.90, 7.54], p = 0.079). Main news source was associated with the stated response to a hypothetical 20% weekly loss (Monte Carlo p = 0.042; Cramer's V = 0.261). The evidence therefore indicates widespread perceived exposure to sentiment cues, but it does not establish a broad causal impact on investment behaviour. Better-validated scales, probability sampling, objective transaction data, and longitudinal designs are required.

Keywords: Generation Z; Investor Sentiment; Social Media; FOMO; Cryptocurrency; Fintech; Investment Behaviour; Artificial Intelligence.

INTRODUCTION

Investment decisions do not occur in an informational vacuum. Prices, headlines, peer discussions, creator commentary, app notifications, and algorithmically curated feeds jointly shape what an investor notices and how risk is interpreted. Classical market models place strong weight on information processing and rational valuation, whereas behavioural finance shows that beliefs, attention, emotions, and limits to arbitrage can permit sentiment to affect both individual decisions and market outcomes (De Long et al., 1990; Barberis et al., 1998; Baker & Wurgler, 2006; Hirshleifer, 2015). Market sentiment is therefore treated here as a broad state of optimism, pessimism, enthusiasm, or fear that may influence choices beyond what contemporaneous fundamentals alone would justify.

Generation Z has entered investing in an environment of mobile brokerage, fractional shares, cryptocurrency, short-form video, online communities, and rapidly developing AI-based tools. These channels reduce participation costs but also compress the time between attention, interpretation, and trade execution. Evidence from online retail platforms shows that salient attention can induce concentrated buying and subsequent return

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

reversals, while the wider fintech literature emphasizes both broader access and new behavioural risks (Barber & Odean, 2008; Goldstein et al., 2019; Barber et al., 2022; Welch, 2022). A joint FINRA Foundation-CFA Institute report similarly identifies social media, crypto, FOMO, and family as important features of Gen Z investing, providing practical motivation for the present survey (FINRA Investor Education Foundation & CFA Institute, 2023).

The research problem is not simply whether young investors encounter market commentary. It is whether perceived shifts in market mood, repeated creator posts, social-media FOMO, algorithmic recommendations, push notifications, fractional trading, and AI assistance are systematically connected with their reported portfolio choices and reactions to losses. The primary dataset supplied for this study directly asks about these mechanisms. It also contains an important methodological warning: broad agreement with separate statements does not necessarily mean those statements form a reliable psychological scale or predict observed investment categories. This paper accordingly combines descriptive evidence with reliability testing and conservative inferential analysis.

Research problem

Market sentiment is often studied through aggregate indicators, news tone, search volume, message-board text, or returns. Such designs are valuable for identifying market-level relationships but do not always reveal how young retail investors interpret creator repetition, digital nudges, or AI recommendations. Conversely, many Gen Z reports are descriptive and do not test whether sentiment exposure is associated with a concrete choice such as holding crypto or with a specified response to a rapid loss. The present research addresses that gap using primary survey data while explicitly recognizing that a cross-sectional questionnaire can establish association, not causation.

Objectives of the study

- To describe the demographic profile, current investment choices, and principal market-news sources of the respondents.
- To measure the reported prevalence of economic-pressure beliefs, social sentiment susceptibility, digital trading impulsivity, and reliance on AI tools.
- To assess the internal consistency of the proposed multi-item constructs before using composite scores.
- To test whether social sentiment susceptibility is associated with digital trading impulsivity and with crypto/digital-asset ownership.
- To evaluate whether respondents' main news source is related to sentiment scores and to their stated reaction to a hypothetical 20% weekly investment loss.
- To derive practical implications for financial educators, platform designers, regulators, and young investors while identifying the limits of the evidence.

Scope and contribution

The empirical scope is limited to the supplied 2026 survey and the variables recorded in it. The paper contributes by combining four elements in one analysis: (i) market and creator sentiment; (ii) platform nudges and fractional trading; (iii) AI-supported investment analysis and portfolio delegation; and (iv) actual self-reported asset categories plus a loss-response scenario. It also contributes a transparent data-quality audit, worked statistical calculations, effect sizes, confidence intervals, robustness checks, and graphical representations.

REVIEW OF LITERATURE

Investor sentiment and behavioural finance

The efficient-markets benchmark assumes that prices reflect available information, but behavioural models show why non-fundamental beliefs may persist. Noise-trader risk can deter arbitrageurs from immediately

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

correcting mispricing (De Long et al., 1990). Barberis et al. (1998) model underreaction and overreaction through representativeness and conservatism, while Daniel et al. (1998) link overconfidence and biased self-attribution to predictable return patterns. Baker and Stein (2004) interpret market liquidity as a sentiment indicator, and Brown and Cliff (2005) connect investor sentiment with asset valuation. Baker and Wurgler (2006, 2007) further show that sentiment effects are stronger for securities that are difficult to value or arbitrage.

At the individual level, prospect theory predicts reference dependence and greater sensitivity to losses than to comparable gains (Kahneman & Tversky, 1979). This framework is directly relevant to panic selling, holding losses, and risk seeking after bad economic news. Odean (1998) documents the disposition effect, and Barber and Odean (2000) show that excessive trading can damage individual-investor performance. Shiller's (2017) narrative-economics approach extends the analysis by explaining how contagious stories can organize expectations and economic action. Together, these theories suggest that market mood can affect both perceived opportunity and perceived danger.

Attention, media, and online sentiment

Attention is a scarce resource. Barber and Odean (2008) show that individual investors are disproportionately drawn to attention-grabbing stocks, and Da et al. (2011) use search intensity to measure investor attention. Media is not merely a passive mirror: Engelberg and Parsons (2011) provide evidence that local media exposure changes trading, while Tetlock (2007) links pessimistic media language with market activity and returns. Internet message boards likewise contain information about volatility and market disagreement (Antweiler & Frank, 2004), and aggregate Twitter mood has been connected with subsequent market direction (Bollen et al., 2011). Sprenger et al. (2014) find associations among tweet sentiment, returns, message volume, trading volume, disagreement, and volatility.

Mobile interfaces can amplify this attention channel. Barber et al. (2022) find that Robinhood users engage in attention-induced trading and that intense buying of the most popular stocks is followed by negative abnormal returns. Welch (2022), however, shows that retail crowds can also contain information, which cautions against treating all socially influenced trading as irrational. The relevant question is therefore conditional: which forms of attention improve discovery and participation, and which encourage impulsive, poorly researched trades?

Social influence, herding, and echo chambers

Social interaction can lower information costs and make participation more attractive. Hong et al. (2004) show that socially connected households are more likely to enter the stock market. Information cascades provide a mechanism through which individuals rationally follow earlier actions even when their private information differs (Bikhchandani et al., 1992). At the same time, peer interaction can transmit behavioural bias: access to an investment-specific social network nearly doubled the disposition effect in Heimer's (2016) study.

Online networks add selection and personalization. Cookson and Niessner (2020) document persistent disagreement within an investor social network, and Cookson et al. (2023) show that users selectively follow confirmatory viewpoints, producing echo chambers associated with trading behaviour and lower ex post returns. These findings motivate survey items on repeated creator posts, trust in creators, FOMO, and algorithmic recommendations. They also imply that the effect of information source may appear more clearly in a stressful decision scenario than in a broad average score.

FOMO, cryptocurrency, and speculative choice

Fear of missing out is a motivational state involving concern that others are experiencing rewarding opportunities without oneself (Przybylski et al., 2013). In investment settings, FOMO can convert social observation into urgency. Gerrans et al. (2023) find a stronger association between FOMO and crypto ownership than between FOMO and conventional stock ownership, with financial literacy and risk tolerance playing distinct roles. Brokerage evidence also indicates that cryptocurrency traders differ in trading style and

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

performance (Hasso et al., 2019). These findings support analyzing crypto ownership separately rather than combining crypto, stocks, and diversified funds into one undifferentiated risk category.

Financial literacy, fintech, and AI advice

Financial literacy influences participation, diversification, and the ability to evaluate risk. Van Rooij et al. (2011) show that lower literacy is associated with reduced stock-market participation and greater reliance on informal sources. Lusardi and Mitchell (2014, 2023) frame financial literacy as an economically important form of human capital, making it a likely confounder in any study of sentiment and young-investor choices. The present questionnaire does not measure financial literacy, so omitted-variable bias must be acknowledged.

Automated advice may either discipline or intensify behavioural tendencies. D'Acunto et al. (2019) find that robo-advice can improve diversification and reduce some biases for previously undiversified investors, but adoption also changes attention and trading. Brenner and Meyll (2020) show that robo-advisors may substitute for human advice, particularly when investors are concerned about conflicts or fraud. Ajzen's (1991) theory of planned behaviour additionally suggests that attitude, perceived social norms, and perceived control can jointly shape intention. In the current setting, AI analysis and willingness to delegate a portfolio may reflect perceived control and trust, but the two concepts need not behave as a single latent construct.

Research gap

Four gaps guide this study. First, much sentiment research uses market-level text or price data rather than primary responses from young investors. Second, attention, FOMO, app nudges, fractional shares, and AI advice are often studied separately. Third, descriptive claims about Gen Z are not always linked to formal hypothesis testing or effect sizes. Fourth, weak measurement reliability is frequently hidden when survey items are aggregated. This paper addresses these gaps by testing an integrated primary-data model and reporting when the measures do not justify strong latent-construct claims.

Conceptual Framework and Hypotheses

The conceptual framework treats economic pressure, social sentiment susceptibility, and AI reliance as potential correlates of digital trading impulsivity. It also treats crypto ownership as a concrete high-volatility investment choice and the hypothetical 20% loss response as a categorical behavioural outcome. Main market-news source is examined as a contextual factor that may shape both perceived sentiment and loss response.

Table 1. Conceptual variables and operational definitions

Construct or outcome	Operational definition	Items/coding
Economic pressure	Belief that uncertain goals and adverse economic news justify grater risk or high volatility assets.	Q1-Q3; mean of available complete items, 1-4.
Social Sentiment Susceptibility	Responsiveness to creator repetition, creator trust, FOMO and algorithmic risk cues	Q4-Q7; respondent mean, 1-4
Digital trading impulsivity	Unresearched notification-triggered trades, fractional-share speculation, and app-facilitated panic selling.	Q8-Q10;respondent mean, 1-4
AI reliance	Use of AI for trend analysis and willingness to delegate portfolio management to an AI agent.	Q11-Q12; respondent mean, 1-4

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Crypto ownership	Selection of crypto/digital assets among current investments.	1 = selected; 0 = not selected
Loss response	Stated action after a hypothetical 20% weekly portfolio loss.	Sell, wait, buy more, or follow online advice

Hypotheses

H1: Social sentiment susceptibility is positively associated with digital trading impulsivity.

H2: Economic pressure is positively associated with digital trading impulsivity.

H3: AI reliance is positively associated with digital trading impulsivity.

H4: Respondents holding crypto/digital assets report higher social sentiment susceptibility than non-holders.

H5: Main market-news source is associated with the response to a hypothetical 20% weekly loss.

H6: Mean social sentiment susceptibility differs across main market-news-source groups.

RESEARCH METHODOLOGY

Research design and data source

A quantitative, cross-sectional, descriptive-correlational design was used. The supplied CSV contained 92 Google-form-style records collected from 20 August to 2 September 2026 (GMT+5:30). The file included respondent names, age category, occupation, current investment selections, principal market-news source, twelve four-point behavioural items, and one hypothetical loss-response question.

Recruitment method, sampling frame, geography, gender, income, education, financial literacy, prior investment experience, and consent documentation were not included in the dataset. Accordingly, the sample is treated as non-probability and self-selected, and external generalization is limited.

Data cleaning and analytical sample

Names and timestamps were excluded from substantive analysis. Seven raw rows shared the same name and an identical answer profile and were submitted within approximately thirteen minutes. The earliest record was retained and six exact repeats were removed, producing an analytical sample of 86. No other responses were deleted. One behavioural item was missing for one respondent; therefore, analyses involving the economic-pressure composite used 85 complete cases. The loss-response item had one missing record after cleaning (valid n = 85). No values were imputed.

The investment question permitted multiple selections. Eighteen respondents selected both 'I do not currently invest' and at least one asset category. The literal asset selections were retained for transparent multi-response frequencies. For the regression control, a respondent was classified as an active investor if any of direct stocks, mutual funds/ETFs/traditional savings, or crypto/digital assets was selected. This rule avoids erasing stated asset holdings, but the contradiction remains a measurement limitation.

Table 2. Data-quality audit and case flow

Check	Result	Analytical treatment
Raw records	92	Starting dataset

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Exact repeat submissions	6	Removed; earliest identical record retained
Final analytical sample	86	Used for descriptive analysis
Confirmed ages 17-22	73	Used in sensitivity analysis
Age marked Other	13	Retained; exact Gen Z status cannot be verified
Missing Q3	1	Complete-case n = 85 when economic pressure used
Missing loss response	1	Chi-square valid n = 85
Contradictory investment selections	18	Retained and explicitly flagged

Measurement

The behavioural statements were recorded as integers 1-4. Because the CSV did not include the response anchors, the analysis uses the conventional interpretation 1 = strongly disagree, 2 = disagree, 3 = agree, and 4 = strongly agree. This assumption should be verified against the original questionnaire before formal publication. Likert's (1932) scaling logic supports ordinal attitude measurement, but means and regression coefficients are treated as approximate interval summaries, with rank-based tests reported where appropriate.

Composite score for respondent i: $C_i = \frac{1}{k}\sum_{j=1}^{k} x_{ij}$

Each composite required complete responses for all component items. The four-item social-sentiment score, for example, was the mean of creator-shift belief, creator trust, FOMO peak purchase, and algorithmic risk perception. Internal consistency was assessed before interpreting any composite. Cronbach's (1951) alpha is informative for reflective scales, but a low value can also indicate that conceptually broad items behave as heterogeneous or formative indicators.

Statistical analysis

Frequencies and percentages described categorical variables. Means, sample standard deviations, medians, 95% confidence intervals, and agreement percentages summarized the four-point items. Construct means were compared with the mathematical midpoint of 2.5 using one-sample t tests, with Holm correction across four tests; Wilcoxon signed-rank tests served as ordinal robustness checks.

Spearman rank correlations assessed bivariate associations among the four composites, with Holm adjustment across six pairwise tests. A Welch independent-samples t test compared social sentiment between crypto holders and non-holders. A univariable binary logistic regression estimated the odds of holding crypto per one-point increase in social sentiment. Digital trading impulsivity was regressed on social sentiment, economic pressure, AI reliance, and active-investor status using ordinary least squares with HC3 heteroskedasticity-consistent standard errors. Variance inflation factors assessed collinearity.

One-way ANOVA and a Kruskal-Wallis robustness test compared social sentiment across news-source groups. Main news source and hypothetical loss response were cross-tabulated. Because 6 of 16 expected cells were below five, the chi-square statistic was calibrated with 20,000 random permutations of the outcome labels in addition to the asymptotic p value. All tests were two-sided at alpha = 0.05. Effect sizes and confidence intervals were prioritized over significance labels.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Mathematical formulas

$$\text{Percentage} = \frac{f}{N_v} \times 100$$

Mean; $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$

Sample SD: $$s = \sqrt{\frac{\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}}{n-1}}$$

Cronbach alpha = $$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{j=1}^{k} s_j^2}{s_T^2}\right)$$

where k is the number of items, s_j^2 is the variance of item j, and s_T^2 is the variance of the total scale score.

Spearman rank Correlation = $\rho_s = \text{Cor}\left[R(X), R(Y)\right]$

The coefficient was calculated from the ranked variables using average ranks for tied observations.

Welch's Independent sample t test = $$t = \frac{\bar{x}_1 - \bar{x}_0}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_0^2}{n_0}}}$$

The approximate degrees of freedom are: $$\nu = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_0^2}{n_0}\right)^2}{\frac{\left(s_1^2/n_1\right)^2}{n_1 - 1} + \frac{\left(s_0^2/n_0\right)^2}{n_0 - 1}}$$

Ordinary Latest Square model: $DII_i = \beta_0 + \beta_1 SSI_i + \beta_2 EP_i + \beta_3 AI_i + \beta_4 Active_i + \varepsilon_i$

where DII is the dependent investment-intensity measure, β_0 is the intercept, β_1– β_4 are regression coefficients, and ε_i is the error term.

Binary logistic regression = $$\ln\left(\frac{P(Crypto_i = 1)}{1 - P(Crypto_i = 1)}\right) = \beta_0 + \beta_1 SSI_i$$

The odds ratio associated with a one-unit increase in SSI is:

Pearson's Chi-square Test = $$\chi^2 = \sum_r \sum_c \frac{(O_{rc} - E_{rc})^2}{E_{rc}}$$

Cramer's V = $$V = \sqrt{\frac{\chi^2}{N \times \min(r-1, c-1)}}$$

One way ANOVA = $$F = \frac{MS_{\text{between}}}{MS_{\text{within}}}$$ Where,

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

$$MS_{\text{between}} = \frac{SS_{\text{between}}}{k-1}$$

$$MS_{\text{within}} = \frac{SS_{\text{within}}}{N-k}$$

The effect size was estimated using eta-squared:

$$\eta^2 = \frac{SS_{\text{between}}}{SS_{\text{total}}}$$

RESULTS

Respondent profile

Among the 86 cleaned records, 29 respondents (33.7%) were aged 17-18, 22 (25.6%) were aged 19-20, and 22 (25.6%) were aged 21-22. Thirteen (15.1%) selected 'Other,' so exact age and Gen Z eligibility could not be verified for that subgroup. Employment was the largest occupation category (32.6%), followed by self-employment/business (27.9%), students (22.1%), and other/not currently working (17.4%).

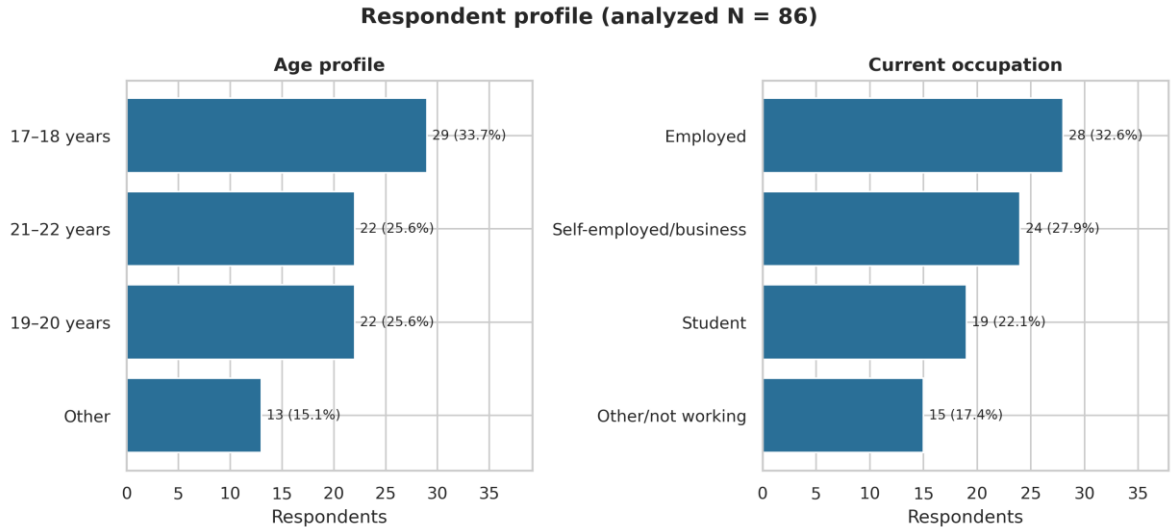


Figure 1. Age and occupation profile of the cleaned analytical sample.

Table 3. Respondent profile and principal market-news source (N = 86)

Variable	Category	N	%
Age	17–18 years	29	33.7%
	19–20 years	22	25.6%
	21–22 years	22	25.6%
	Other	13	15.1%
Occupation	Employed (Full-time / Part-time)	28	32.6%
	Self-Employed / Freelancer / Business	24	27.9%

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

	Student	19	22.1%
	Other / Not currently working	15	17.4%
Main news source	Financial News Outlets (e.g., Bloomberg, Moneycontrol)	26	30.2%
	Social Media & Short Videos (Reels, Shorts)	25	29.1%
	Online Communities (Reddit, Telegram, Discord, X)	23	26.7%
	Friends, Family, or AI Tools	12	14.0%

Investment choices and information sources

Direct stocks and mutual funds/ETFs/traditional savings were each selected by 31 respondents (36.0%), while 24 (27.9%) selected crypto/digital assets. The non-investor option was selected by 29 respondents (33.7%), but 18 of these records also selected at least one investment category. These percentages therefore describe item selection, not mutually exclusive portfolios, and they sum to more than 100%.

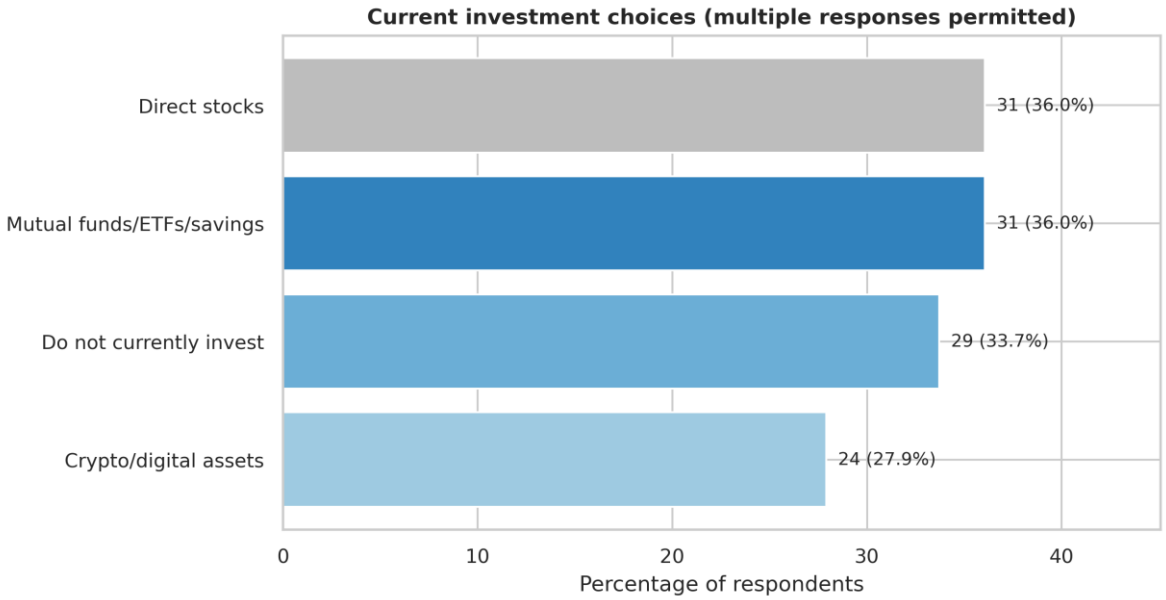


Figure 2. Self-reported current investment choices; multiple responses were permitted.

Financial news outlets were the principal source for 26 respondents (30.2%), social media and short video for 25 (29.1%), online communities for 23 (26.7%), and friends, family, or AI tools for 12 (14.0%). The distribution shows that digital-social sources collectively dominate when social media and online communities are considered together, although the categories cannot isolate the role of AI because AI was combined with friends and family in one response option.

Item-level descriptive results

The strongest agreement concerned fractional shares and market hype: 90.7% agreed or strongly agreed that fractional shares increase their willingness to speculate, with a mean of 3.291. Eighty-six percent agreed that uncertain long-term goals make safe savings feel insufficient, and the same proportion agreed that adverse inflation or economic news increases the desire to take larger risks for quick gains. Notification-triggered unresearched trading was endorsed by 84.9%, while 83.7% reported that social-media FOMO had caused a purchase near a market peak.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Table 4. Item-level descriptive statistics

Item	Short label	n	Mean	SD	Agree/Strongly agree
Q1	Uncertain goals	86	3.081	0.800	86.0%
Q2	Bad news -> bigger risks	86	3.081	0.884	86.0%
Q3	Volatility as necessity	85	2.847	0.970	75.3%
Q4	Creator posts signal shift	86	2.988	0.901	77.9%
Q5	Trust creators over institutions	86	2.930	0.918	75.6%
Q6	FOMO purchase near peak	86	3.012	0.847	83.7%
Q7	Algorithm changes perceived risk	86	2.895	0.812	77.9%
Q8	Alerts prompt unresearched trades	86	3.105	0.736	84.9%
Q9	Fractional shares enable speculation	86	3.291	0.666	90.7%
Q10	Apps accelerate panic-selling	86	2.837	0.992	72.1%
Q11	Use AI to analyze trends	86	2.953	0.906	80.2%
Q12	Trust AI portfolio agent	86	3.070	0.764	86.0%

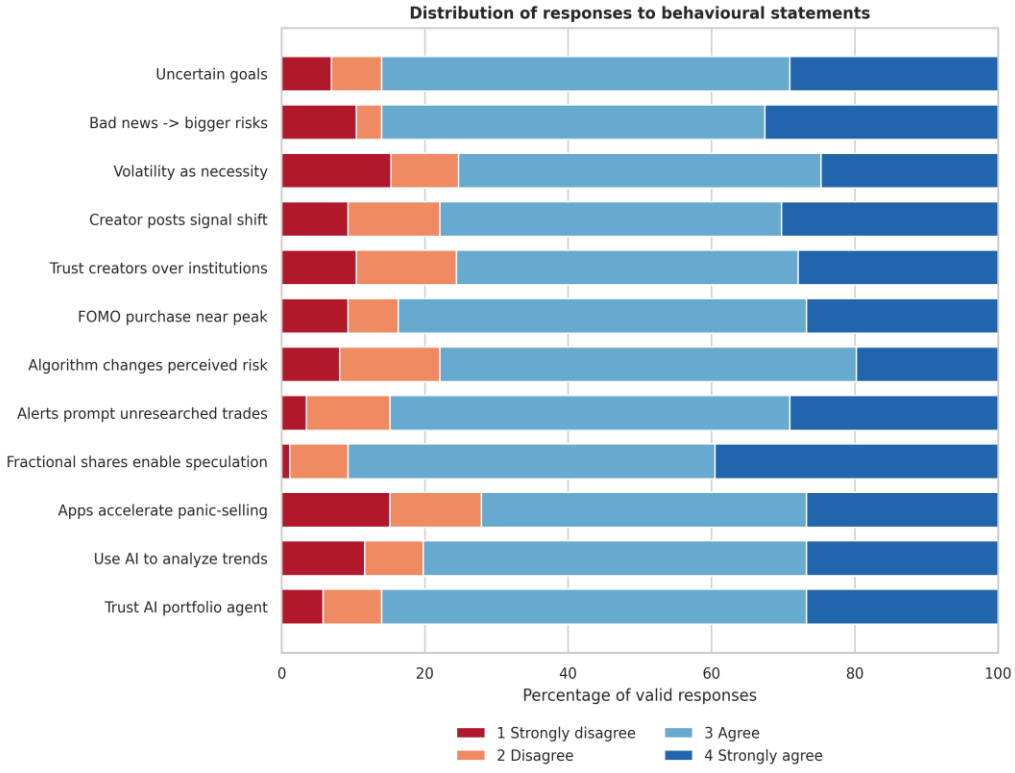


Figure 3. Percentage distribution across the four response categories for all twelve behavioural statements.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Composite scores and measurement reliability

All four composite means exceeded the scale midpoint of 2.5 after Holm correction, and Wilcoxon tests led to the same descriptive conclusion. Digital trading impulsivity had the highest mean (3.078), followed by AI reliance (3.012), economic pressure (3.012), and social sentiment susceptibility (2.956). These high means must be separated from scale quality: coefficient alpha ranged from 0.011 to 0.240, and the alpha for all twelve items was 0.400. Such values do not support treating the item sets as highly coherent reflective latent scales. Composite-based inferential tests are therefore exploratory and may be attenuated by measurement error.

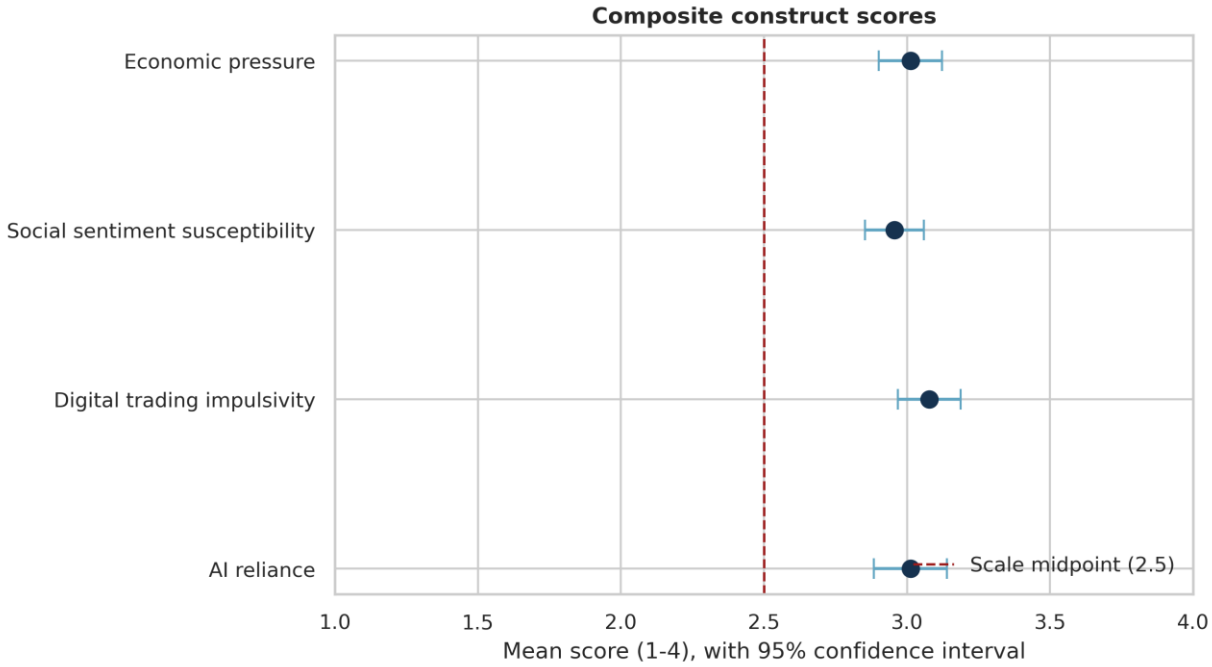


Figure 4. Composite means and 95% confidence intervals relative to the 2.5 scale midpoint.

Table 5. Construct scores, internal consistency, and midpoint tests

Construct	k	n	M	SD	Alpha	t vs. 2.5	Holm p	Cohen d
Economic pressure	3	85	3.012	0.510	0.011	9.245	< 0.001	1.003
Social sentiment susceptibility	4	86	2.956	0.479	0.234	8.831	< 0.001	0.952
Digital trading impulsivity	3	86	3.078	0.510	0.240	10.492	< 0.001	1.131
AI reliance	2	86	3.012	0.599	0.042	7.922	< 0.001	0.854

Correlation analysis

The largest construct-level association was between social sentiment susceptibility and digital trading impulsivity (rho = .157), but it was not statistically significant (unadjusted p = .149; Holm-adjusted p = .892). The remaining correlations ranged from -.053 to .127 and were also non-significant. H1 therefore was not supported by the correlation analysis. The low alpha coefficients imply that these small observed correlations may partly reflect measurement unreliability, but the current data cannot determine the size of that attenuation.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

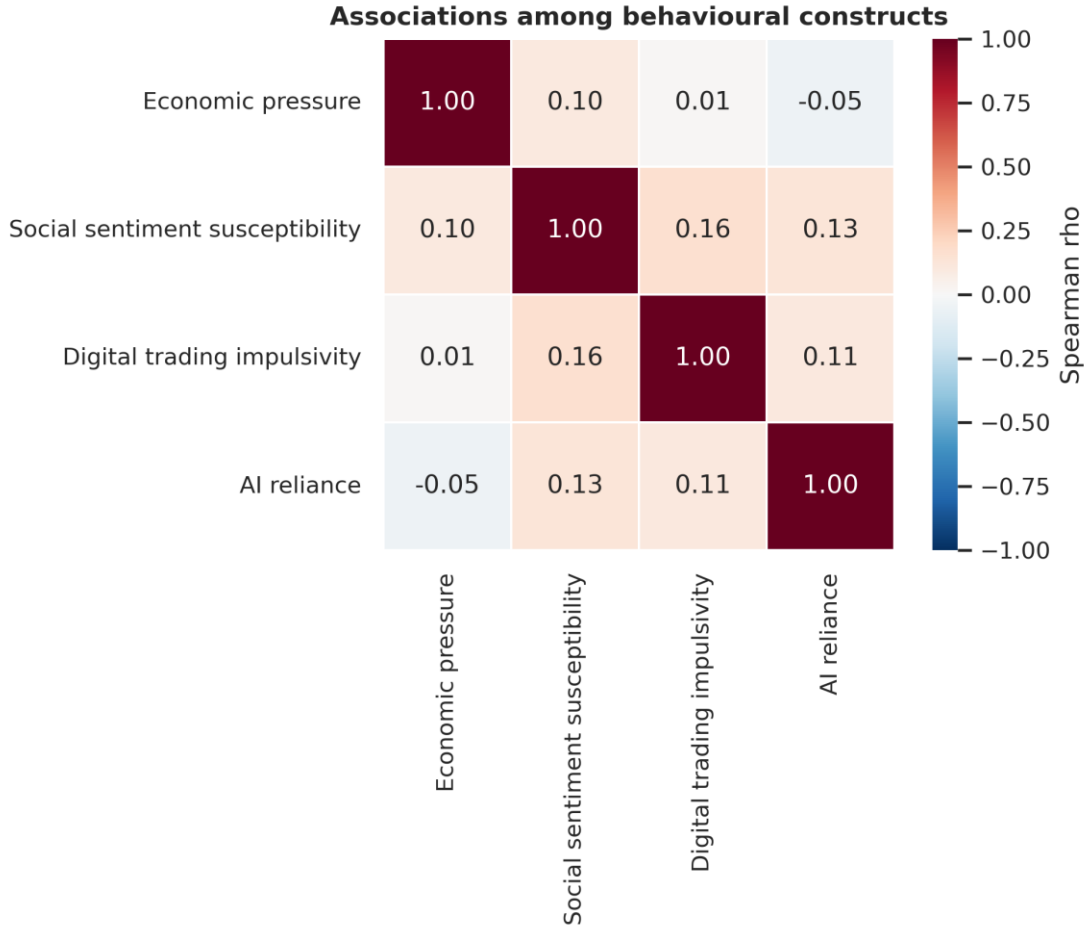


Figure 5. Spearman rank correlations among the four exploratory composite scores.

Table 6. Spearman correlations among composite measures

Variable 1	Variable 2	n	rho	P	Holm p
Economic pressure	Social sentiment susceptibility	85	0.101	0.359	1.000
Economic pressure	Digital trading impulsivity	85	0.009	0.935	1.000
Economic pressure	AI reliance	85	-0.053	0.633	1.000
Social sentiment susceptibility	Digital trading impulsivity	86	0.157	0.149	0.892
Social sentiment susceptibility	AI reliance	86	0.127	0.245	1.000
Digital trading impulsivity	AI reliance	86	0.109	0.317	1.000

Crypto ownership and social sentiment

Crypto holders reported a higher mean social-sentiment score than non-holders (M = 3.104, SD = 0.382, n = 24 versus M = 2.899, SD = 0.503, n = 62). Welch's t(54.84) = 2.032, p = .047, with Hedges g = 0.429. The standardized mean difference was small-to-moderate and narrowly met the 0.05 threshold, providing provisional support for H4. The univariable logistic model was less decisive. A one-point increase in social sentiment corresponded to estimated odds of crypto ownership that were 2.60 times as large, but the 95%

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

confidence interval was wide [0.90, 7.54] and included 1.00 (Wald p = 0.079; likelihood-ratio p = 0.069). McFadden's R-squared was 0.032 and AUC was 0.623. Therefore, the mean comparison suggests a possible relationship, but the prediction is imprecise and not robust to the model-based significance criterion.

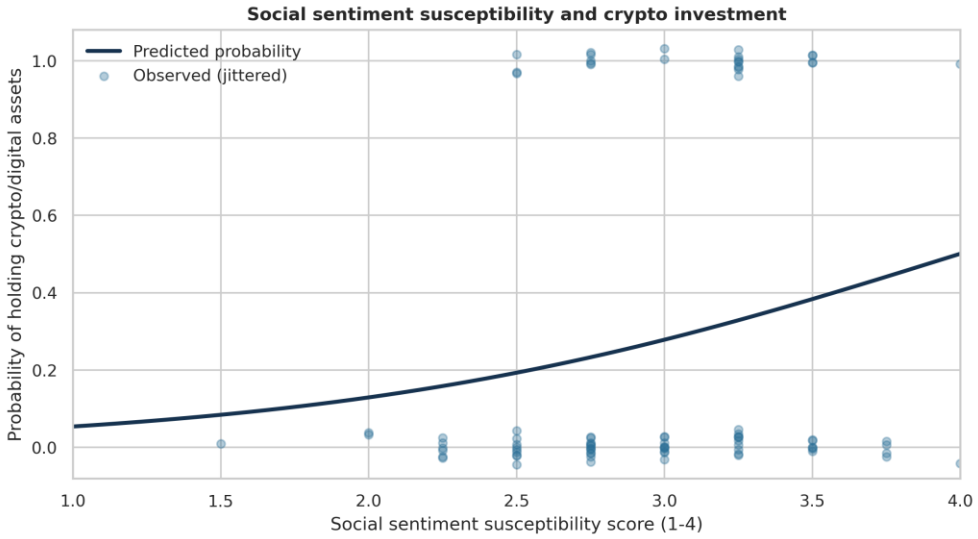


Figure 6. Observed crypto ownership and model-predicted probability across social sentiment scores.

Table 7. Crypto ownership tests

Analysis	Estimate	Uncertainty / test	Interpretation
Welch mean comparison	Difference = 0.205	t(54.84) = 2.032; p = 0.047; g = 0.429	Crypto holders reported higher SSI; exploratory support
Univariable logistic regression	B = 0.956; OR = 2.60	95% OR CI [0.90, 7.54]; p = .079	Positive but imprecise; model p > .05

Multiple regression of digital trading impulsivity

The four-predictor regression used 85 complete cases and explained 6.2% of the variance in digital trading impulsivity (R-squared = 0.062; adjusted R-squared = 0.016). The model was not significant, F(4, 80) = 1.332, p = 0.265. Social sentiment had a positive but non-significant coefficient (B = 0.167, HC3 p = 0.231). Economic pressure, AI reliance, and active-investor status were also non-significant. H1, H2, and H3 were therefore not supported in the adjusted model.

Variance inflation factors ranged from 1.03 to 1.08, showing no problematic predictor collinearity. The Breusch-Pagan test was non-significant (LM = 1.109, p = 0.893), while the Shapiro-Wilk residual test was borderline (W = 0.971, p = 0.049); HC3 standard errors were used to reduce sensitivity to residual assumptions.

Table 8. OLS regression predicting digital trading impulsivity (HC3 standard errors)

Predictor	B	HC3 SE	Std. beta	t	p	95% CI for B
Intercept	2.103	0.741	-	2.838	0.006	[0.628, 3.579]
Social sentiment susceptibility	0.167	0.138	0.157	1.208	0.231	[-0.108, 0.442]

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Economic pressure	0.015	0.122	0.015	0.122	0.903	[-0.228, 0.258]
AI reliance	0.113	0.111	0.133	1.019	0.311	[-0.108, 0.333]
Active investor	0.106	0.219	0.070	0.486	0.628	[-0.329, 0.542]

News source, sentiment, and loss response

Social sentiment scores were highest among respondents naming financial news outlets as their main source (M = 3.144) and lowest among those naming social media/short video (M = 2.790). The omnibus ANOVA approached but did not meet the .05 criterion, F(3, 82) = 2.538, p = 0.062, eta-squared = 0.085. The Kruskal-Wallis robustness test was likewise non-significant, H(3) = 6.604, p = 0.086. No Holm-adjusted pairwise comparison was significant. H6 was not supported.

Table 9. Social sentiment susceptibility by main news source

Main news source	n	Mean	SD
Financial News Outlets (e.g., Bloomberg, Moneycontrol)	26	3.144	0.443
Friends, Family, or AI Tools	12	2.979	0.494
Online Communities (Reddit, Telegram, Discord, X)	23	2.913	0.410
Social Media & Short Videos (Reels, Shorts)	25	2.790	0.524

The stated response to a 20% weekly loss differed by main news source, chi-square (9, N = 85) = 17.413. The asymptotic p value was 0.043; because expected counts were sparse, the primary calibrated result used 20,000 label permutations and remained significant (Monte Carlo p = 0.042). Cramer's V = 0.261, indicating a small-to-moderate association. H5 was supported at the 0.05 level, subject to the observational and hypothetical nature of the response.

The largest contribution to the chi-square statistic came from respondents using online communities who said they would follow social-media/community advice (observed = 10; expected = 4.87). Financial-news users more often chose to wait for recovery (observed = 11; expected = 7.06), while social-media/short-video users more often chose to buy more (observed = 8; expected = 5.29). These are descriptive cell patterns and should not be interpreted as causal effects of source selection.

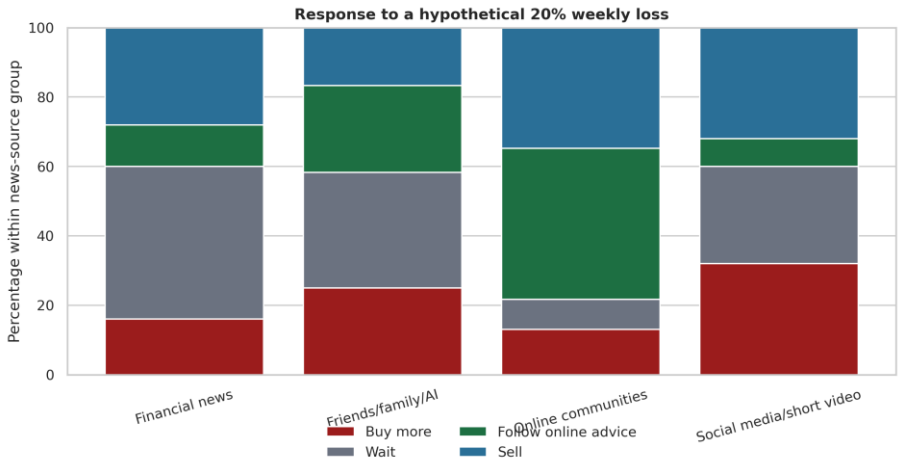


Figure 7. Composition of hypothetical loss responses within each main news-source group.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

Table 10. Observed cross-tabulation: main news source by hypothetical loss response

News source	Buy more	Wait	Follow online advice	Sell	Total
Financial News Outlets (e.g., Bloomberg, Moneycontrol)	4	11	3	7	25
Friends, Family, or AI Tools	3	4	3	2	12
Online Communities (Reddit, Telegram, Discord, X)	3	2	10	8	23
Social Media & Short Videos (Reels, Shorts)	8	7	2	8	25
Column total	18	24	18	25	85

Sensitivity analysis

Because 13 respondents selected 'Other' for age, the key models were repeated among the 73 respondents explicitly aged 17-22. The social-sentiment/digital-impulsivity correlation remained small and non-significant (rho = 0.117, p = 0.326). The adjusted social-sentiment coefficient remained non-significant (B = 0.149, HC3 p = 0.335), and the crypto odds ratio remained positive but imprecise (OR = 2.39, p = 0.168). The substantive interpretation therefore did not depend on retaining the unverified age category.

Worked Mathematical Calculations

This section shows how the reported statistics arise from the cleaned data. Software was used for the complete calculations, but the substitutions below make the analysis auditable. Minor differences may occur if intermediate values are rounded.

Frequency and percentage

There were 29 respondents aged 17-18 among 86 cleaned cases.

Percentage aged 17-18 = (29 / 86) x 100 = 33.7209% = 33.7%

Item mean and standard deviation

For the fractional-share speculation item, the cleaned frequency distribution was: response 1 = 1, response 2 = 7, response 3 = 44, and response 4 = 34. Thus n = 86, SUM x = 1(1) + 2(7) + 3(44) + 4(34) = 283, and SUM x-squared = 1-squared(1) + 2-squared(7) + 3-squared(44) + 4-squared(34) = 969.

Mean = 283 / 86 = 3.2907 = 3.291

$s = \text{sqrt}\{ [969 - 283^2/86] / 85 \} = 0.666$

Agreement combined responses 3 and 4: (44 + 34) / 86 x 100 = 90.70%.

Composite score

For any respondent, the social sentiment susceptibility index (SSI) was calculated as the mean of Q4-Q7.

$SSI_i = (Q4i + Q5i + Q6i + Q7i) / 4$

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

A respondent answering 3, 3, 4, and 3 would therefore have SSI = (3 + 3 + 4 + 3) / 4 = 3.25. Across the 86 cleaned respondents, the average SSI was 2.956 with SD = 0.479.

Cronbach's alpha

For the four SSI items, k = 4, the sum of item variances was 3.030780, and the variance of the four-item total was 3.675103.

$\alpha = [4 / (4 - 1)] \times [1 - 3.030780 / 3.675103] = 0.233761 = 0.234$

For all twelve behavioural items, k = 12, SUM item variances = 8.758263, and total-score variance = 13.833894.

$\alpha_{12} = [12 / 11] \times [1 - 8.758263 / 13.833894] = 0.400$

One-sample midpoint test

For SSI, x-bar = 2.9564, s = 0.4793, n = 86, and the midpoint $\mu 0 = 2.5$.

$t = (2.9564 - 2.5000) / (0.4793 / \sqrt{(86)}) = 8.831$

With df = 85, the unadjusted p value was < 0.001; the Holm-adjusted p value across four midpoint tests was < 0.001. Cohen d = (2.9564 - 2.5) / 0.4793 = 0.952.

Welch t test

$t = (3.1042 - 2.8992) / \sqrt{(0.3825^2/24 + 0.5030^2/62)} = 2.032$

The Welch-Satterthwaite degrees of freedom were 54.84. The two-sided p value was 0.047; the small-to-moderate bias-corrected standardized difference was Hedges g = 0.429.

Multiple regression

The fitted equation, using unstandardized coefficients, was:

Predicted DII = 2.103 + 0.167(SSI) + 0.015(EP) + 0.113(AI) + 0.106(Active)

The total sum of squares was 22.0837 and the residual sum of squares was 20.7049, so regression sum of squares = 1.3787.

$R^2 = 1 - (20.7049 / 22.0837) = 0.0624$

$F = (1.3787 / 4) / (20.7049 / 80) = 0.3447 / 0.2588 = 1.332$

This F statistic gave p = 0.265. For SSI, B = 0.167 and HC3 SE = 0.138, giving t = 1.208 and p = 0.231.

Logistic regression and odds ratio

logit(p_crypto) = -3.8189 + 0.9556(SSI)

OR per one-point SSI increase = exp (0.9556) = 2.600

For illustration, the predicted probability is 0.129 at SSI = 2, 0.278 at SSI = 3, and 0.501 at SSI = 4. The confidence interval for the odds ratio, exp[0.9556 +/- 1.96(0.5433)], is [0.897, 7.541], demonstrating substantial uncertainty.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

One-way ANOVA

For the four news-source groups, SS_between = 1.658969 and SS_within = 17.865013; df_between = 3 and df_within = 82.

MS_between = 1.658969 / 3 = 0.552990

MS_within = 17.865013 / 82 = 0.217866

F = 0.552990 / 0.217866 = 2.538; η^2 = 1.658969 / 19.523983 = 0.085

Chi-square and Cramer's V

For the financial-news x buy-more cell, the row total was 25, the column total was 18, and N = 85.

Expected count E = (25 x 18) / 85 = 5.294

Cell contribution = $(4 - 5.294)^2$ / 5.294 = 0.316

Summing the corresponding contributions across all sixteen cells gave chi-square = 17.413 with df = (4 - 1)(4 - 1) = 9.

Cramer's V = √{17.4129 / [85 x min(3, 3)]} = √(17.4129 / 255) = 0.261

Because 6 of 16 expected counts were below five, a fixed-margin-preserving label-permutation procedure was used. In 20,000 random permutations, the calibrated p estimate was 0.0422.

DISCUSSION

Interpretation of the descriptive pattern

The survey presents a striking descriptive picture: most respondents endorsed the idea that uncertain goals, negative economic news, creator repetition, FOMO, app alerts, fractional shares, and AI tools affect their investment thinking. This aligns with the literature on limited attention and salient stocks (Barber & Odean, 2008; Da et al., 2011), online sentiment transmission (Antweiler & Frank, 2004; Bollen et al., 2011; Sprenger et al., 2014), and socially amplified investment urgency (Heimer, 2016; Gerrans et al., 2023). Fractional shares produced the highest agreement, which is consistent with the proposition that lower transaction thresholds can broaden access while also making speculative participation easier.

However, average endorsement is not the same as predictive structure. Respondents could agree with several independently worded risks without the items moving together across individuals. That is exactly what the low alpha coefficients show. For example, using AI to analyze trends and trusting an AI agent to manage a portfolio are behaviourally distinct: one is decision support and the other is delegation. Likewise, buying after bad news, buying near a peak because of FOMO, and selling after a loss reflect different directions of response. Their conceptual relationship does not guarantee internal consistency.

Sentiment, impulsivity, and crypto choice

H1-H3 were not supported. Social sentiment, economic pressure, and AI reliance did not independently predict the broad digital-impulsivity composite after controlling for active-investor status. This does not prove that sentiment is irrelevant. The sample can reliably detect only moderate correlations (approximately |r| = 0.30 with 80% power at two-sided alpha = 0.05), and low measurement reliability further reduces power. The appropriate conclusion is narrower: the present instrument and sample do not provide robust evidence of a general cross-item pathway from sentiment susceptibility to digital trading impulsivity.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

The crypto result is more suggestive. Crypto holders had a higher mean sentiment score with $p = 0.047$ and $g = 0.429$, consistent with Gerrans et al. (2023) and with evidence that crypto trading attracts distinctive behavioural profiles (Hasso et al., 2019). Yet the logistic confidence interval was very wide and the Wald p value exceeded 0.05. The relationship should therefore be described as preliminary rather than confirmed. It could reflect FOMO, risk tolerance, financial literacy, income, prior experience, or self-selection into crypto - none of which can be separated with the current variables.

News source and behaviour under loss

The clearest inferential finding involved the hypothetical loss response. Online-community users were disproportionately likely to say they would follow online advice after a 20% weekly loss, whereas financial-news users more often preferred to wait. This accords with research showing that social networks can shape participation and bias (Hong et al., 2004; Heimer, 2016) and that personalized networks may generate disagreement and echo chambers (Cookson & Niessner, 2020; Cookson et al., 2023). Nevertheless, source choice is endogenous: individuals may choose channels that match their existing preferences. The chi-square result therefore indicates association, not source-induced behaviour.

The absence of a significant ANOVA difference in social sentiment by news source is also informative. People who rely on formal financial news may still consume creator content and experience FOMO, while people who name social media as their main source may be skeptical of particular creators. A single 'main source' question cannot measure exposure intensity, credibility judgments, cross-platform use, or algorithmic personalization. Future work should separate frequency, trust, source diversity, and active versus passive consumption.

Theoretical implications

The findings favour a conditional rather than universal account of market sentiment. Prospect theory and the disposition effect explain why the framing of losses matters (Kahneman & Tversky, 1979; Odean, 1998), while attention models explain which assets enter the decision set (Barber & Odean, 2008). Social learning and information cascades explain why the same signal may be reinforced by peers (Bikhchandani et al., 1992; Hong et al., 2004). The current data suggest these mechanisms may appear in specific choices - particularly crypto ownership and crisis response - without forming one stable general trait.

The AI items also support a distinction between analytical assistance and autonomous delegation. Robo-advice can improve diversification and reduce some behavioural biases (D'Acunto et al., 2019), but adoption depends on trust and perceived conflicts (Brenner & Meyll, 2020). Combining AI use with friends and family in the news-source question prevents a clean test of AI-specific influence. A future instrument should distinguish generative-AI consultation, conventional robo-advice, automated execution, and human verification.

Practical implications

For financial educators, the high endorsement of app-driven and sentiment-driven behaviours indicates a need for pre-trade checklists, source verification, diversification exercises, and explicit teaching about loss framing. Financial literacy is not only knowledge of interest and inflation; it also includes the discipline to pause when attention and urgency are being engineered (Lusardi & Mitchell, 2014, 2023).

For platforms, design choices such as repeated alerts, trending lists, celebratory animations, and frictionless fractional orders should be evaluated for their behavioural effects. A protective design could require a brief risk summary, diversification warning, cooling-off option, or confirmation that the user has reviewed fundamental information before a high-volatility purchase. The evidence from attention-induced retail trading shows why user-interface features deserve empirical scrutiny (Barber et al., 2022).

For regulators and consumer-protection bodies, the news-source/loss-response association suggests that financial promotion rules should cover creators and communities, not only traditional advertising. Disclosures should be visible at the point of recommendation, and young investors should understand conflicts of interest,

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue IX September 2026

paid promotion, and the difference between popularity and evidence. For AI tools, outputs should communicate uncertainty, limitations, and the need for licensed professional advice where appropriate.

CONCLUSION

The primary survey shows that market-sentiment cues are highly visible in the investment lives of the respondents. Large majorities agreed that economic uncertainty, creator content, FOMO, app notifications, fractional shares, and AI tools affect their risk perceptions or actions. Yet the data do not support a simple conclusion that one stable sentiment trait broadly drives Gen Z investment behaviour. The proposed scales were weakly reliable, the social-sentiment correlation with digital impulsivity was small and non-significant, and the adjusted regression explained little variance.

Two narrower findings deserve follow-up. Crypto holders reported moderately higher sentiment susceptibility, although logistic uncertainty prevented a firm predictive conclusion. Main news source was associated with the chosen response to a hypothetical severe weekly loss, with online-community users disproportionately likely to follow online advice. These results suggest that sentiment may matter most through specific channels and decision contexts rather than as a universal influence.

Accordingly, the study's central contribution is both substantive and methodological: it identifies widespread perceived exposure to sentiment while demonstrating the importance of reliability testing, data-quality checks, effect sizes, and cautious causal language. For educators and platforms, the practical priority is to strengthen deliberate decision processes before urgency becomes action. For researchers, the priority is a better-validated, longitudinal design that connects measured exposure with objective portfolio behaviour.

Hypothesis Summary

Table 11. Summary of hypothesis tests

Hypothesis	Primary evidence	Decision
H1: SSI positively associated with DII	rho = .157, p = .149; adjusted B = .167, p = .231	Not supported
H2: Economic pressure predicts DII	Adjusted B = .015, p = .903	Not supported
H3: AI reliance predicts DII	Adjusted B = .113, p = .311	Not supported
H4: Crypto holders have higher SSI	Welch p = .047, g = .429; logit OR = 2.60, p = .079	Provisional / mixed
H5: News source associated with loss response	Monte Carlo p = .042; Cramer's V = .261	Supported
H6: SSI differs by news source	ANOVA p = .062; Kruskal-Wallis p = .086	Not supported

REFERENCES

1. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T
2. Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. Journal of Finance, 59(3), 1259-1294. https://doi.org/10.1111/j.1540-6261.2004.00662.x

3. Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. Journal of Financial Markets, 7(3), 271-299. https://doi.org/10.1016/j.finmar.2003.11.005
4. Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. Journal of Finance, 61(4), 1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x
5. Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic Perspectives, 21(2), 129-152. https://doi.org/10.1257/jep.21.2.129
6. Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance, 55(2), 773-806. https://doi.org/10.1111/0022-1082.00226
7. Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21(2), 785-818. https://doi.org/10.1093/rfs/hhm079
8. Barber, B. M., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-induced trading and returns: Evidence from Robinhood users. Journal of Finance, 77(6), 3141-3190. https://doi.org/10.1111/jofi.13183
9. Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. Journal of Financial Economics, 49(3), 307-343. https://doi.org/10.1016/S0304-405X(98)00027-0
10. Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992-1026. https://doi.org/10.1086/261849
11. Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1-8. https://doi.org/10.1016/j.jocs.2010.12.007
12. Brenner, L., & Meyll, T. (2020). Robo-advisors: A substitute for human financial advice? Journal of Behavioral and Experimental Finance, 25, 100275. https://doi.org/10.1016/j.jbef.2020.100275
13. Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and asset valuation. Journal of Business, 78(2), 405-440. https://doi.org/10.1086/427633
14. Cookson, J. A., & Niessner, M. (2020). Why don't we agree? Evidence from a social network of investors. Journal of Finance, 75(1), 173-228. https://doi.org/10.1111/jofi.12852
15. Cookson, J. A., Engelberg, J. E., & Mullins, W. (2023). Echo chambers. Review of Financial Studies, 36(2), 450-500. https://doi.org/10.1093/rfs/hhac058
16. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16, 297-334. https://doi.org/10.1007/BF02310555
17. Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. Journal of Finance, 66(5), 1461-1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x
18. D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The promises and pitfalls of robo-advising. Review of Financial Studies, 32(5), 1983-2020. https://doi.org/10.1093/rfs/hhz014
19. Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. Journal of Finance, 53(6), 1839-1885. https://doi.org/10.1111/0022-1082.00077
20. De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy, 98(4), 703-738. https://doi.org/10.1086/261703
21. Engelberg, J. E., & Parsons, C. A. (2011). The causal impact of media in financial markets. Journal of Finance, 66(1), 67-97. https://doi.org/10.1111/j.1540-6261.2010.01626.x
22. FINRA Investor Education Foundation, & CFA Institute. (2023). Gen Z and investing: Social media, crypto, FOMO, and family. https://www.finrafoundation.org/research-center/gen-z-and-investing-social-media-crypto-fomo-and-family
23. Gerrans, P., Abisekaraj, S. B., & Liu, Z. (2023). The fear of missing out on cryptocurrency and stock investments: Direct and indirect effects of financial literacy and risk tolerance. Journal of Financial Literacy and Wellbeing, 1(1), 103-137. https://doi.org/10.1017/flw.2023.6
24. Goldstein, I., Jiang, W., & Karolyi, G. A. (2019). To FinTech and beyond. Review of Financial Studies, 32(5), 1647-1661. https://doi.org/10.1093/rfs/hhz025
25. Hasso, T., Pelster, M., & Breitmayer, B. (2019). Who trades cryptocurrencies, how do they trade it, and how do they perform? Evidence from brokerage accounts. Journal of Behavioral and Experimental Finance, 23, 64-74. https://doi.org/10.1016/j.jbef.2019.04.009

26. Heimer, R. Z. (2016). Peer pressure: Social interaction and the disposition effect. Review of Financial Studies, 29(11), 3177-3209. https://doi.org/10.1093/rfs/hhw063
27. Hirshleifer, D. (2015). Behavioral finance. Annual Review of Financial Economics, 7, 133-159. https://doi.org/10.1146/annurev-financial-092214-043752
28. Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. Journal of Finance, 59(1), 137-163. https://doi.org/10.1111/j.1540-6261.2004.00629.x
29. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263-292. https://doi.org/10.2307/1914185
30. Likert, R. (1932). A technique for the measurement of attitudes. Archives of Psychology, 140, 1-55. https://legacy.voteview.com/pdf/Likert_1932.pdf
31. Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. Journal of Economic Literature, 52(1), 5-44. https://doi.org/10.1257/jel.52.1.5
32. Lusardi, A., & Mitchell, O. S. (2023). The importance of financial literacy: Opening a new field. Journal of Economic Perspectives, 37(4), 137-154. https://doi.org/10.1257/jep.37.4.137
33. Odean, T. (1998). Are investors reluctant to realize their losses? Journal of Finance, 53(5), 1775-1798. https://doi.org/10.1111/0022-1082.00072
34. Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. Computers in Human Behavior, 29(4), 1841-1848. https://doi.org/10.1016/j.chb.2013.02.014
35. Shiller, R. J. (2017). Narrative economics. American Economic Review, 107(4), 967-1004. https://doi.org/10.1257/aer.107.4.967
36. Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014). Tweets and trades: The information content of stock microblogs. European Financial Management, 20(5), 926-957. https://doi.org/10.1111/j.1468-036X.2013.12007.x
37. Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. Journal of Finance, 62(3), 1139-1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x
38. Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. Journal of Financial Economics, 101(2), 449-472. https://doi.org/10.1016/j.jfineco.2011.03.006
39. Welch, I. (2022). The wisdom of the Robinhood crowd. Journal of Finance, 77(3), 1489-1527. https://doi.org/10.1111/jofi.13128