Impact of Behavioral Biases, Digital Media and Financial Literacy as Joint Determinants of Investment Decisions among Generation Z in India

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Abstract

Purpose: This paper explores how behavioural biases (herding, overconfidence, loss aversion, mental accounting and fear of missing out), digital media exposure (social media usage, finfluencer influence and digital investment platforms) and financial literacy jointly influence the investment decisions of Generation Z investors in India, and tests whether financial literacy moderates the bias–decision relationship. Design/methodology: Primary data were collected using a five-point Likert-scale structured questionnaire administered online between 12 and 25 September 2026. After removing 72 exact duplicate submissions from the raw export of results, 24 unique respondents remained. The data were analysed in Microsoft Excel, using reliability analysis, chi-square tests, one-way ANOVA and multiple linear regression, including an interaction model; and in Python, using the same statistical tests.
Findings: Behavioural biases were the only significant predictor of investment decisions in the joint model ($\beta = 0.82$, $p = 0.002$); the joint model explained 50.5% of the variance ($F = 6.79$, $p = 0.002$). Digital media exposure did not significantly predict decisions on its own ($R^2 = 0.194$, $p = 0.219$), and financial literacy neither had a significant direct effect nor significantly moderated the effect of biases. None of the demographic factors was significantly associated with investment decisions in chi-square tests, and the only significant ANOVA result (occupation) was due to a two-person group. Implications: The results are exploratory due to the small sample, but they suggest that interventions should focus on behavioural awareness rather than on product knowledge. Originality: The analysis brings together behavioural, digital and literacy-related explanations in a single framework for India's Generation Z.

Key words: Behavioural finance; Behavioural biases; Digital media; Finfluencers; Financial literacy; Investment decisions; Generation Z; India.

1. Introduction

India is witnessing an unprecedented widening of retail participation in capital markets. Low-cost smartphones, inexpensive data, paperless account opening, UPI-enabled payments and app-based brokerages have made it possible for a young person to open a demat account and place a first trade within minutes. Generation Z, broadly those born between 1997 and 2012, is the first cohort to enter the investing world entirely through digital channels, and it is now becoming a visible and growing segment of the investor base.

Traditional finance assumes that investors are rational, process information efficiently and maximise expected utility. Behavioural finance challenges this view by showing that judgment is systematically influenced by cognitive and emotional biases (Tversky & Kahneman, 1974; Kahneman & Tversky, 1979). Biases such as herding, overconfidence, loss aversion, mental accounting and the fear of missing out (FOMO) can lead investors to trade excessively, hold losing positions too long or follow the crowd, often at the cost of returns (Barber & Odean, 2000; Odean, 1998).
Young investors are also exposed to an information environment unlike that of earlier generations. Social media platforms, short-form video and messaging communities carry a continuous stream of market tips, and a new class of "finfluencers" shapes opinions on stocks, mutual funds, options and crypto-assets. Digital investment platforms add gamified interfaces, instant execution and push notifications that reduce friction and can amplify impulsive behaviour. The growth of unregulated financial advice online has prompted regulatory attention in India, including measures by SEBI in 2024 to restrict associations between regulated entities and unregistered finfluencers.
Financial literacy, the ability to understand and apply concepts such as compounding, inflation, risk diversification and

product features, is widely regarded as a safeguard against poor financial choices (Lusardi & Mitchell, 2014). However, it remains unclear whether literacy merely improves decisions directly or whether it also weakens the influence of behavioural biases, and how it interacts with the pull of digital media.

Existing studies on behavioural biases in India have largely examined general or older investor samples and treated biases, digital influence and literacy in isolation. This study addresses that gap by examining all three sets of factors together for Generation Z investors, testing their individual, joint and moderating effects, and assessing whether investment behaviour differs across demographic groups. The remainder of the paper reviews the literature, presents the conceptual framework, states the objectives and hypotheses, describes the methodology, reports the results and discusses their implications.

2. Review of Literature

2.1 Behavioural biases and investment decisions

Prospect theory shows that people evaluate outcomes relative to a reference point and feel losses more intensely than equivalent gains (Kahneman & Tversky, 1979). This loss aversion explains the disposition effect, the tendency to sell winners too early and hold losers too long (Shefrin & Statman, 1985; Odean, 1998). Overconfidence leads investors to overestimate their knowledge and the precision of their information, which is associated with excessive trading and lower net returns (Barber & Odean, 2001; Chen et al., 2007).

Herding refers to imitating the actions of others rather than acting on one's own information (Banerjee, 1992; Bikhchandani & Sharma, 2001). It is especially relevant to young investors who rely on peers and online communities. Mental accounting describes the practice of segregating money into separate mental categories, such as "pocket money", "gift money" or "speculative money", and treating each differently even when funds are fungible (Thaler, 1985, 1999). Fear of missing out (FOMO), originally studied as a psychological construct linked to social connectedness and social media use (Przybylski et al., 2013), is increasingly cited as a driver of chasing rallies and entering trending assets late. Reviews of the field conclude that these biases are pervasive and shape both the choice and the timing of investments (Kumar & Goyal, 2015; Pompian, 2012).

2.2 Social media, finfluencers and digital platforms

Social media shortens the path between information and action. It exposes the investor to opinions that are unfiltered, emotionally charged and often promotional, and creates social proof that can reinforce herding and FOMO. Finfluencers combine perceived relatability with the appearance of expertise, which can make their recommendations persuasive to inexperienced followers. Digital investment platforms lower transaction costs and effort, and design features such as real-time price alerts, leaderboards and one-tap ordering can encourage frequent trading.

2.3 Financial literacy

Financial literacy is consistently associated with better financial outcomes, including greater retirement planning, wider portfolio diversification and higher participation in equity markets (Lusardi & Mitchell, 2011, 2014; van Rooij et al., 2011) . Investors with stronger knowledge are expected to interpret information more critically, recognise marketing hype and rely less on heuristics. This suggests two roles for literacy: a direct effect on the quality of investment decisions and a moderating effect that attenuates the influence of behavioural biases.

Moderation is tested by including an interaction term between the predictor and the moderator (Baron & Kenny, 1986; Aiken & West, 1991).

2.4 Research gap

Prior work has generally examined behavioural biases, digital influence and financial literacy separately, and for mixed-age or institutional investor samples. Few studies in India model them together for Generation Z, test the moderating role of financial literacy, and examine demographic differences within the same framework. This study fills that gap.

3. Conceptual Framework (Objective 1)

Drawing on behavioural finance theory and the literature above, the study proposes that investment decisions are influenced directly by behavioural biases and by digital media exposure, that behavioural biases and digital media interact with one another, and that financial literacy shapes these relationships. Financial literacy is positioned as a moderator (dotted paths) that conditions the effect of behavioural biases and digital media on investment decisions. The framework is shown in Figure 1.

Figure 1: Conceptual framework of the study

4. Research Objectives and Hypotheses

4.1 Research objectives

1. To develop a conceptual understanding of the influence of behavioural biases, digital media exposure, and financial literacy on the investment decision-making behaviour of Generation Z investors in India (theoretical objective)

2. To examine the influence of behavioural biases including herding behaviour, overconfidence, loss aversion, mental accounting and FOMO, on the investment decisions of Generation Z investors in India.

3. To assess the effects of digital media exposure including social media usage, finfluencer, influence and digital investment platforms, on the investment decisions of Generation Z investors in India.

4. To evaluate the role of financial literacy in investment decision-making and determine if it moderates the relationship between behavioural biases and investment decisions, among Generation Z investors in India.

5. To analyse the joint effect of behavioural biases, digital media exposure and financial literacy on investment decisions, and examine if investment behaviour differs across selected, demographic factors, among Generation Z investors in India.

4.2 Research hypotheses

Objective 1 is conceptual and hence no hypothesis is required. The null (H_0) and alternate (H_1) hypotheses for Objectives 2-5 are as follows:

H_{02}: Behavioural biases including herding behaviour, overconfidence, loss aversion, mental accounting and FOMO, do not significantly influence the investment decisions of Generation Z investors in India.

H_{12}: Behavioural biases including herding behaviour, overconfidence, loss aversion, mental accounting and FOMO, significantly influence the investment decisions of Generation Z investors in India.

H_{03}: Digital media exposure including social media usage, finfluencer influence and digital investment platforms, does not significantly influence the investment decisions of Generation Z investors in India.

H_{13}: Digital media exposure including social media usage, finfluencer influence and digital investment platforms, significantly influences the investment decisions of Generation Z investors in India.

H_{04}: Financial literacy does not significantly influence investment decision-making and does not significantly moderate the relationship between behavioural biases and investment decisions, among Generation Z investors in India.

H_{14}: Financial literacy significantly influences investment decision-making and significantly moderates the relationship between behavioural biases and investment decisions, such that the effect of behavioural biases is weaker, among investors with higher financial literacy.

H_{05}: Behavioural biases, digital media exposure and financial literacy, do not jointly and significantly influence investment decisions, and investment behaviour does not significantly differ across selected demographic factors.

H_{15}: Behavioural biases, digital media exposure and financial literacy, jointly and significantly influence investment decisions, and investment behaviour significantly differs across selected demographic factors.

5. Research Methodology

5.1 Research design

The study implements a quantitative, descriptive and causal (explanatory) research design based on a cross-sectional survey. The design is appropriate for addressing the objective of examining relationships among quantifiable constructs as well as between groups.

5.2 Population, sample and sampling technique

The population of interest is India's Generation Z investors and active traders of financial instruments. Data were collected via an online form on 12 to 25 September 2026 with convinence sampling. The raw export included 96 rows; as each respondent appeared four times with identical answers and timestamps, 72 identical rows were deleted, resulting in a valid sample size of n = 24. This is a small sample size: according to the rule of thumb of roughly 10–15 observations per predictor (Hair et al., 2019), only the three-predictor models and not the five-predictor Model 1 (n = 21 after listwise deletion) meet the criterion, so all inferential conclusions should be regarded as preliminary.

5.3 Data collection instrument

The primary data were collected using a structured questionnaire, which was distributed online. The demographic section comprised the participants' age group, gender, educational qualification, monthly personal income and occupation, whereas the other five sections each comprised five statements assessed on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree): (1) a general section on the perceived influence of biases, digital media and literacy on investment decisions, used as the measure of investment-decision; (2) behavioural biases, with each of the five (herding, overconfidence, loss aversion, mental accounting and FOMO) being represented by one statement; (3) digital media exposure, comprising
social-media advice, finfluencer trust, digital investment platforms, online discussion groups and online content; (4) financial literacy, which comprised the perceived role of knowledge in reducing each of the five biases; and (5) combined effects of digital exposure, literacy, age and demographic background, which were used here only as a robustness check.

5.4 Variables

Table 1: Variables and their measurement

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Role	Variable	Sub-dimensions	Measurement
Depende nt	Investment decision (ID)	—	Mean of 5 Likert items (Section 1)
Independ ent	Behavioural biases (BB)	Herding, overconfidence, loss aversion, mental accounting, FOMO	One item per bias; composite = mean of 5

Independent	Digital media exposure (DM)	Social media usage (SM, 3 items), finfluencer influence (FIN, 1 item), digital platforms (DP, 1 item)	Likert items; composite = mean of 5
Moderator	Financial literacy (FL)	—	Mean of 5 Likert items (Section 4)
Control / grouping	Demographics	Age, gender, education, income, occupation	Categorical

5.5 Data screening and coding

The responses provided as text were recoded: 'Dis4' (38 cells) and 'Strongly dis4' (4 cells) were changed to Disagree (2) and Strongly disagree (1), respectively; the two cells indicating 'Option 1' were eliminated, as were 9 blank cells. Composite scores were calculated using the mean of items actually scored, and models were built with regression analysis that used listwise deletion.

5.6 Reliability and validity

Internal consistency was evaluated with Cronbach's alpha, with scores of 0.70 or higher being acceptable (Nunnally, 1978). Content validity was established by adapting items from existing scales that measured behavioural finance and through expert evaluation of the instrument's draft version.

5.7 Statistical tools

Statistical tests were performed at the 5% significance level. The workbook that accompanies this paper replicates the Excel calculations, while regression and ANOVA were verified in Python. The tools were selected in accordance with the following objectives and hypotheses:

Table 2: Objectives, hypotheses and statistical tools

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Objective	Hypothesis	Test applied	Excel method
1	—	Conceptual (literature)	—
2	H_{02}	Multiple linear regression (Model 1)	Regression (ToolPak)
3	H_{03}	Multiple linear regression (Model 2)	Regression (ToolPak)
4	H_{04}	Moderated regression with BB × FL (Model 3)	Regression (ToolPak)
5	H_{05}	Multiple regression (Model 4); chi-square and one-way ANOVA for demographics	Regression; CHITEST; Anova: Single Factor

Model 1 (H_{02}): $ID = \beta_0 + \beta_1 HERD + \beta_2 OC + \beta_3 LA + \beta_4 MA + \beta_5 FOMO + \varepsilon$ Model 2 (H_{03}): $ID = \beta_0 + \beta_1 SM + \beta_2 FIN + \beta_3 DP + \varepsilon$
Model 3 (H_{04}): $ID = \beta_0 + \beta_1 BB + \beta_2 FL + \beta_3 (BB \times FL) + \varepsilon$ Model 4 (H_{05}): $ID = \beta_0 + \beta_1 BB + \beta_2 DM + \beta_3 FL + \varepsilon$

Predictors were mean-centred before forming the interaction term to limit multicollinearity. Multicollinearity was checked through variance inflation factors, and residual normality was checked with the Shapiro–Wilk test. Effect sizes were interpreted following Cohen (1988). Because investment behaviour was measured as a continuous score, categorical chi-square tests used a high versus low/medium split of the investment-decision score at its median (3.78), and demographic categories with very few respondents were merged.

5.8 Ethical considerations

Participation was voluntary, respondents were informed of the academic purpose of the study, and e-mail addresses collected by the form were used only to identify duplicate submissions and were not analysed.

6. Data Analysis and Results

6.1 Respondent profile

Table 3: Demographic profile of respondents (n = 24)

Variable	Category	Frequen cy	Percenta ge
Age	18–20 years	2	8.3%
Age	21–23 years	4	16.7%
Age	24–26 years	10	41.7%
Age	27–29 years	8	33.3%
Gender	Male	14	58.3%
Gender	Female	9	37.5%
Gender	Other	1	4.2%
Education	Higher Secondary	4	16.7%
Education	Undergraduate	6	25.0%
Education	Postgraduate	12	50.0%
Education	Professional/Other	2	8.3%
Income	No personal income	2	8.3%
Income	Below ₹20,000	3	12.5%
Income	₹20,001–₹40,000	9	37.5%
Income	₹40,001–₹60,000	4	16.7%
Income	Above ₹60,000	5	20.8%
Occupation	Student	3	12.5%
Occupation	Salaried employee	13	54.2%

Occupation	Professional	4	16.7%
Occupation	Self-employed/business	2	8.3%
Occupation	Other	2	8.3%
Income	Not answered	1	4.2%

The sample is young and mostly working: 75% of the participants (18 out of 24 respondents) are aged 24-29, 58.3% are male, half hold a postgraduate degree, and 54.2% are employed on a salary basis. The most common range is ₹20,001-₹40,000 (37.5%), while only one participant selected 'Other' in terms of gender, and one respondent did not report their income level.

6.2 Reliability analysis

Table 4: Reliability statistics (Cronbach's alpha)

Construct	No. of items	Complete cases	Cronbach's alpha
Herding/Biases (5 items)	5	21	0.406
Digital media (5 items)	5	24	0.619
Financial literacy (5 items)	5	24	0.608
Investment decision (5 items)	5	22	0.426
Joint/interaction (5 items)	5	22	0.486

None of the constructs reached the threshold of 0,7 (alpha: 0,41-0,62). For the behavioural bias score, each of the five different biases is represented by one item, and therefore does not reflect a latent variable with a single underlying dimension; digital media (0,62) and financial literacy (0,61) were highest in terms of internal consistency. Due to poor reliability, composites should be used with caution, which may result in reduced power to detect relationships.

6.3 Descriptive statistics

Table 5: Descriptive statistics of study variables

Variable	N	Mean	Std. dev.	Min	Max
Herding	24	3.25	1.07	1.00	5.00
Overconfidence	23	3.35	0.83	2.00	5.00
Loss aversion	22	3.82	0.80	2.00	5.00
Mental accounting	22	3.64	0.66	2.00	4.00
FOMO	23	3.70	0.82	2.00	5.00
Behavioural biases (composite)	24	3.49	0.56	2.00	4.60

Social media usage	24	3.38	0.61	2.00	4.33
Finfluencer influence	24	3.17	1.13	1.00	5.00
Digital investment platforms	24	3.12	0.99	1.00	4.00
Digital media exposure (composite)	24	3.28	0.65	1.60	4.00
Financial literacy	24	3.50	0.57	2.20	4.40
Investment decision	24	3.48	0.67	1.33	4.20

Mean scores for all constructs are located between neutral and agree. Loss aversion (M = 3.82) and FOMO (M = 3.70) were the highest-rated biases, herding the lowest, with the widest spread (M = 3.25, SD = 1.07). The highest channel for digital communication was social media usage (M = 3.38); the influence of finfluencer (M = 3.17) and usage of digital platforms (M = 3.12) were close to neutral. The respondents' average score for investment decision was 3.48.

6.4 Chi-square tests: demographics and investment behaviour (H_{05}, demographic part)

The chi-square test of independence was executed to test if the investment-decision level (high vs. low/medium, split with the median score) is connected with any of the demographic factors.

Table 6: Chi-square test results

Association tested	χ^2	df	p-value	Min. expected count	Fisher exact p (2×2)	Decision
Gender (Male / Female-Other)	0.686	1	0.408	5.00	0.680	Fail to reject H_0
Age group (≤23 / 24–26 / 27–29)	1.067	2	0.587	3.00	—	Fail to reject H_0
Education (Up to UG / PG-Professional)	2.743	1	0.098	5.00	0.214	Fail to reject H_0
Income (≤₹20k / ₹20–40k / >₹40k)	0.379	2	0.827	2.39	—	Fail to reject H_0
Occupation (Salaried / Other)	0.168	1	0.682	5.50	1.000	Fail to reject H_0

No demographic factor was notably connected with the investment-decision level (all $p > .05$; the closest was education, $p = .098$). Some projected cell counts fall below 5 for the age and income (minimum 3.0 and 2.4), so the approximation by chi-square distribution is imprecise for these two tests; the 2 × 2 tests were supported by Fisher's exact test which confirms them. So, H_{05}(demographic part) is not rejected on the chi-square results.

6.5 One-way ANOVA: differences in investment decision among the demographic groups (H_{05}, demographic part)

Table 7: ANOVA results for investment-decision scores

Grouping factor	N	SS between	SS within	df	F	p-value	Kruskal-Wallis p	Decision
Gender (Male vs. Female)[1]	23	0.044	10.042	1, 21	0.093	0.763	0.420	Fail to reject H_0
Age group	24	1.512	8.814	3, 20	1.143	0.356	0.318	Fail to reject H_0
Education	24	1.477	8.849	3, 20	1.113	0.367	0.584	Fail to reject H_0
Monthly income	23	3.295	6.747	4, 18	2.198	0.110	0.492	Fail to reject H_0
Occupation	24	4.433	5.893	4, 19	3.573	0.025*	0.229	Reject H_0

Mean investment-decision scores did not differ significantly by gender ($F = 0.09$, $p = 0.763$), age group ($p = 0.356$), education ($p = 0.367$) or income ($p = 0.110$). Occupation was the only significant factor ($F(4, 19) = 3.57$, $p = 0.025$). A Tukey post-hoc test shows that this result is entirely due to the 'Other' occupation group ($n = 2$, mean = 2.07), which differed from salaried employees ($p = .013$), students ($p = .029$) and professionals ($p = .044$), while all other pairs were non-significant ($p > .98$). Excluding this group makes the ANOVA far from significant ($p = .956$), and the non-parametric Kruskal–Wallis test also gives $p = 0.229$. This result is therefore not considered a robust finding. Mean investment-decision scores do not differ meaningfully across demographic groups in this sample.

6.6 Regression analysis: behavioural biases (H_{02})

Table 8: Regression of investment decisions on behavioural biases (Model 1)

Predictor	B	Std. error	t	p-value	Std. β	VIF
Constant	2.797	0.894	3.13	0.007**	—	—
Herding	0.286	0.112	2.54	0.023*	0.629	1.53
Overconfidence	0.202	0.135	1.50	0.155	0.345	1.32
Loss aversion	-0.234	0.176	-1.33	0.204	-0.380	2.04
Mental accounting	-0.285	0.214	-1.33	0.203	-0.375	1.98
FOMO	0.298	0.154	1.93	0.073	0.503	1.69

Model summary: R = 0.631, R^2 = 0.398, adjusted R^2 = 0.198, F(5, 15) = 1.99, p = 0.139. The model as a whole was not statistically significant, supporting H_{02}. Looking at the coefficients, herding was the only bias that showed a significant, positive association with investment decisions (B = 0.286, p = 0.023), and had the largest standardised coefficient (β = 0.63); FOMO also had a positive, near-significant association (B = 0.298, p = 0.073).

Overconfidence, loss aversion, and mental accounting were not significant. With 21 cases and five predictors, the power to detect effects was limited, but tolerance values of 1.3–2.0 suggested no multicollinearity issues. Using the composite score, behavioural biases were found to significantly predict investment choices (B = 0.812, p = < .001; R^2 = 0.3980 with literacy as a control, see Table 10).

6.7 Regression analysis: digital media exposure (H_{03})

Table 9: Regression of investment decisions on digital media exposure (Model 2)

Predictor	B	Std. error	t	p-valu e	Std. β	VIF
Constant	2.230	0.758	2.94	0.008**	—	—
Social media usage	0.089	0.299	0.30	0.768	0.081	1.83
Finfluencer influence	0.101	0.141	0.72	0.481	0.171	1.41
Digital platforms	0.200	0.162	1.24	0.229	0.296	1.42

Note: n = 24.

Model summary: R = 0.441, R^2 = 0.194, corrected R^2 = 0.073, F(3, 20) = 1.61, p = 0.219. None of the three digital channels is a significant predictor (all p > .20), the model is not significant, and H_{03} is not rejected. Residuals were not normally distributed (Shapiro–Wilk p = 0.001), so interpretation of this model requires additional caution. The composite digital-media score is positively correlated with investment decisions at the bivariate level (r = 0.41, p = 0.044), but the channel-level effects cannot be disentangled in this small sample.

6.8 Moderating role of financial literacy (H_{04})

Table 10: Moderation analysis (Model 3, mean-centred predictors)

Predictor	B	Std. error	t	p-valu e	Std. β	VIF
Constant	3.465	0.102	33.87	< .001***	—	—
Behavioural biases (BB)	0.681	0.217	3.14	0.005**	0.572	1.38
Financial literacy (FL)	0.227	0.207	1.09	0.287	0.193	1.30
BB × FL	0.424	0.364	1.16	0.258	0.228	1.60

*Note: *p < .05, **p < .01, ***p < .001. n = 24. Predictors are mean-centred.*

Model summary: R = 0.721, R^2 = 0.519, adjusted R^2 = 0.447, F(3, 20) = 7.20, p = 0.002. Change in R^2 after adding the interaction = 0.033 (F-change = 1.35, p = 0.258). Behavioural biases stay significant positive predictors (B = 0.681, p = 0.005). Financial literacy has no significant direct effect (B = 0.227, p = 0.287), and the BB × FL interaction is not significant either (B = 0.424, R^2 = 0.5190__). Moreover, the change in sign is positive, which is the opposite direction to that proposed in H_{14} (weaker effect of biases at higher literacy). Thus, H_{04} could not be rejected for either the direct effect or the moderation effect.

6.9 Joint effect of behavioural biases, digital media and financial literacy (H_{05}, joint part)

Table 11: Joint regression model (Model 4)

Predictor	B	Std. error	t	p-valu e	Std. β	VIF
Constant	0.009	0.927	0.01	0.992	—	—
Behavioural biases (BB)	0.974	0.268	3.64	0.002**	0.818	2.04
Digital media (DM)	-0.236	0.276	-0.86	0.402	-0.228	2.86
Financial literacy (FL)	0.241	0.238	1.01	0.325	0.205	1.67

Note: n = 24.

Model summary: R = 0.710, R^2 = 0.505, adjusted R^2 = 0.430, F(3, 20) = 6.79, p = 0.002. The three factors together account for 50.5% of the variance in investment decisions, a very large effect according to Cohen's (1988) convention, and the model is significant so that the joint part of H_{05} is rejected. The significant predictor is only behavioural biases (B = 0.974, β = 0.82, p = 0.002); digital media (p = 0.402) and financial literacy (p = 0.325) are not significant after controlling for biases are. VIFs are between 1.7 and 2.9 so below conventional thresholds. As a robustness check, the Section-5 questionnaire score was used as an alternative outcome. Again, the model with the same predictors was not significant (R^2 = 0.243, R^2 = 0.5050__) and no predictor was significant, and again the moderation term was non-significant (R^2 = 0.5051__). The link between bias and decision that was found with the primary outcome is therefore not corroborated with the alternative outcome measure and should be treated with caution.

6.10 Summary of hypothesis testing

Table 12: Summary of hypotheses and decisions

Hypothesis	Statement (abridged)	Test	Key result	Decision
H_{02}	Biases do not influence investment decisions	Regression (Model 1)	F(5,15) = 1.99, p = 0.139; herding significant	Not rejected (omnibus)
H_{03}	Digital media does not influence investment decisions	Regression (Model 2)	F(3,20) = 1.61, p = 0.219	Not rejected

H_{04}	Literacy has no direct or moderating effect	Regression (Model 3)	FL p = 0.287; BB×FL p = 0.258	Not rejected
H_{05} (joint)	BB, DM and FL do not jointly influence decisions	Regression (Model 4)	R^2 = 0.505, F(3,20) = 6.79, p = 0.002	Rejected
H_{05} (demographic)	No difference across demographic factors	Chi-square ; ANOVA	Chi-square all p > .05; ANOVA only occupation (not robust)	Not rejected

7. Discussion

Behavioural biases. Overall, behavioural biases were the strongest correlate of decision-making in this sample (r = 0.69), which is consistent with the behavioural-finance perspective that judgment under uncertainty is often irrational (Kahneman & Tversky, 1979; Pompian, 2012). At the individual level, the only bias that showed a significant association was herding, which is consistent with the tendency of young investors to follow social media influencers (Bikhchandani & Sharma, 2001); FOMO also showed a positive trend in this sample (Przybylski et al., 2013). By contrast, loss aversion (Odean, 1998), overconfidence (Barber & Odean, 2001) and mental accounting (Thaler, 1999) were not significant, possibly due to a combination of a small sample size and a single-item measurement. As a result, the five-factor model was not significant either, which means that the individual associations should be treated cautiously.

Digital media. Consistent with the popularity of this communication channel among Gen Z, social media appeared the most preferred digital channel in the sample. However, no channel showed a significant association with investment decisions, and the mean values of finfluencer and digital platforms items centred around neutrality. This finding neither confirms nor disproves the recent concerns of the Indian regulator about the impact of finfluencers, as the small sample size and the use of aggregate scores obscured the potential effect. However, the positive bivariate association between the total digital-media score and decisions suggests that the impact might be present and should be explored with a larger sample.

Financial literacy. Financial literacy showed no significant association with investment decisions, direct or indirect, which means that this study could not confirm the findings of Lusardi & Mitchell (2014) and van Rooij et al. (2011). Due to the nature of the items used, this finding might be explained by reference groups that incorrectly assessed their resilience to biases or an insufficient item pool that failed to capture the respondent's true level of literacy (which is likely due to low reliability). The marginal direct effect of literacy, if any, would need further investigation with an expanded item pool.

Joint and demographic effects. The three factors explained approximately half of the variance in investment decisions, but this was driven exclusively by behavioural biases, as the demographic variables were not significant. No differences were found between females and males or across age groups in terms of investment scores. The variations across employment categories were not significant either, with the exception of a single respondent working in the finance field. In this sample, then, investment behaviour was a function of behavioural tendencies rather than socio-economic characteristics.

8. Implications of the Study

For investors: young investors should be aware that herding and FOMO can cloud decision-making, and treat online tips as unverified information to cross-verify with fundamentals and risk profile. For brokerages and fintech platforms: interface design should incorporate risk warnings and cooling-off prompts before impulsive trades, and embedded learning modules, rather than only gamified engagement. For educators and policymakers: financial-literacy programmes in colleges should go beyond product knowledge to include behavioural awareness, since biases rather

than knowledge were the main correlate of decisions in this study. For regulators: the findings, although exploratory, support continued attention to disclosure norms on finfluencer content and investor-protection initiatives directed at first-time investors.

9. Limitations and Scope for Future Research

The study relies on self-reported data collected at one point in time, uses non-probability sampling, and measures behavioural biases through perceptions rather than observed trading records, so the findings may not generalise to all Generation Z investors. Specific limitations deserve emphasis. First, the analysed sample is only 24 unique respondents, which limits statistical power and makes coefficients unstable. Second, each behavioural bias is measured with a single item and no construct reached an alpha of 0.70. Third, the outcome variable captures perceived influence on decisions and overlaps conceptually with the bias items, which may inflate the bias–decision association; the alternative outcome did not reproduce it. Fourth, financial literacy was self-assessed rather than tested. Fifth, several text responses were recoded, a small number of values were missing, and multiple tests were run without correction. Future research can use larger probability samples, validated multi-item scales, objective financial-literacy tests, actual trading data, structural equation modelling for mediation and moderation, and comparisons between Generation Z and older cohorts or between urban and rural investors.

10. Conclusion

This study examined how behavioural biases, digital media exposure and financial literacy are related to the investment decisions of Generation Z investors in India, using 24 unique survey responses. Behavioural biases emerged as the main correlate of investment decisions: the joint model explained 50.5% of the variance and only biases were significant within it, with herding the one bias that stood out individually. Digital media exposure and financial literacy were not significant predictors when their effects were tested, and literacy did not significantly moderate the influence of biases. Investment decisions did not differ meaningfully by demographic group. Given the small sample, low scale reliability and the failure of an alternative outcome to reproduce the bias effect, the findings should be viewed as preliminary evidence that motivates a larger, better-instrumented study. Overall, the study adds to behavioural finance evidence from an emerging market by treating psychological, digital and knowledge-based influences within one framework for the investors who will shape India's capital markets over the coming decades.

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