

Beyond Traditional Biases: An Exploratory Empirical Study of Emerging Emotional and Situational Drivers of Investment Behaviour among Gen Z Investors in Bhopal, India

Mr. Rahul Kumar Vishwakarma¹, Prof. (Dr.) Kuldeep Agnihotri²,

¹Research Scholar, School of Commerce, Devi Ahilya Viswavidyalaya, Indore, (M.P.)

²Director / Principal, ISBA Group of Institutes, Indore, (M.P.)

ABSTRACT - The research seeks to explore and determine emerging micro-emotional, psychological, and situational triggers and drivers that influence and shape the investment behaviour of young Gen Z investors in the current scenario, beyond existing traditional behavioural biases. In which research adopted a quantitative research design, using a structured questionnaire with a 5-point Likert scale to collect primary data from Gen Z (Age group between 13 and 29 years) investors in the Bhopal region of the Indian subcontinent. The authors used Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) in JAMOV Software, and SmartPLS 4 for PLS-SEM (Partial Least Squares Structural Equation Modelling) for measurement and structural model assessment. The studies found some novel and micro emerging drivers beyond traditional biases, i.e. socially driven impulsive investment and financially informed and seeking financial growth factors among Gen Z investors, which contribute significantly to influencing their investment behaviour and decisions. The findings of this study contribute to the existing body of knowledge in the field of behavioural finance by adding new micro dimensions that play a significant role, along with traditional biases in behavioural investing in the Indian context.

Key Words: Gen Z investors, Investment behaviour, Emotional drivers, Situational factors, Traditional Biases

1. INTRODUCTION

Traditionally, investment decisions were analyzed based on classical finance theories such as Modern Portfolio Theory (Markowitz, 1952) and the Efficient Market Hypothesis (Fama, 1970), which assume that investors are rational, risk-averse and judgments are made based on past historical data. But over the past

few years, Behavioural finance has emerged in the world of finance and investment, which shows and reveals a paradigm shift among investors to qualitative, behavioural, and psychological aspects of investment, from rational and disciplined investing in traditional finance (Shiller, 2003). People do not make investment decisions on a spreadsheet; they make them at the dinner table, driven by personal history, emotions, and ego (Housel, 2020).

As in the studies on the Indian subcontinent, found that people invest because of emotions, social pressure and attitudes (Arora and Gupta, 2026), where Chandra and Kumar 2012) identified that Psychological heuristics and biases drive the investment behaviour of individuals in the Indian context. (Manzoor et al., 2023) also argued concepts of market efficiency and rationality, and discussed the relevance and importance of behavioural finance by exploring more factors of the investment behaviour of the investors. (Mahmood et al., 2024) investigated the influence of behavioural biases (anchoring bias, risk aversion bias, herding bias, representativeness bias, overconfidence bias, and disposition bias) on individual investing decisions.

In the present study, we want to examine and determine unexplored and novel factors that influence investment behaviour among Gen Z in the Indian context.

2. LITERATURE REVIEW AND HYPOTHESIS

2.1 Related literature

In the existing studies on behavioural finance, (Shah and Khursheed Ahmad Butt, 2024) focus only on classical heuristic biases such as overconfidence, anchoring, representativeness, availability bias and avoid modern biases, emerging, emotional and situational drivers (Hii and Ong, 2025) found Finfluencer and parasocial relationship through social

media, simplifying the investing by providing easy content, avoiding technical jargon, creates financial awareness among Gen Z and millennials for investing. Likewise, (Baker et al., 2021) point out that traditional behavioural finance theories do not adequately account for the dynamic nature of emotions such as fear, excitement, and social validation, particularly in technology-based investment contexts where information is updated in real time, thereby affecting investment decisions. In addition to cognitive biases, "emotional finance" or investor mood, sentiment and psychological state can result in irrational investor behaviour during times of volatility in the market (Nofsinger, 2017). Although the above literature has touched upon herding behaviour, Bikhchandani and Sharma (2001) have not comprehensively explained the heightened effect of digital communities and online platforms that augment peer-driven investment choices of young investors. Statman (2019) extends the approach of behavioural finance by adding an element of expressive and emotional benefits to investing – that is, investors have a desire to get 'pride', 'excitement' and 'identity' out of their investments, an aspect especially relevant to Gen Z.

Moreover, Dhar and Zhu (2006) pay attention to the issues of overconfidence and trading behaviour, but fail to examine the situational factors, including financial pressure, economic uncertainty and lifestyle changes, that can have a huge impact on investment behaviour. In recent research, such as (Kumar et al., 2023), it has been revealed that social media trends, peer approval, and the fear of missing out (FOMO) serve as significant situational and emotional drivers that go beyond the realm of typical cognitive biases, consuming the minds of Gen Z investors. Prendergast et al. (2024) argue that digital nudges, app notifications, and gamification elements in trading platforms foster impulsive investment actions, highlighting situational stimuli's role in financial decision-making.

In the Indian context, Gupta and Singh (2022) discuss the behavioural biases of retail investors but have primarily stuck to traditional frameworks, without elaborating on the changing dynamics of cultural, social media, and regional influences on Gen Z investors. Additionally, Raut et al. (2018) present an analysis of investment intentions based on the Theory of Planned Behaviour, which includes attitude, subjective norms and perceived behavioural control, without considering

emotional volatility and situational factors in the real-time moment.

Previous research tends to examine cognitive and behavioural biases, including overconfidence, herding, and loss aversion. There is, however, little research that has investigated situational and emotional factors like jealousy, boredom, idle funds and income dissatisfaction as direct factors influencing investment behaviour, and how they shape investment behaviour, especially for Gen Z investors in semi-urban areas such as Bhopal City in India.

2.2 Hypothesis development

H1. To assess the impact of social influence and peer-driven impulsiveness on Gen Z investment behaviour.

H2. To assess the impact of financial growth aspiration on Gen Z investment behaviour.

3. METHODOLOGY

3.1 Data and Sample

The study uses primary data obtained from 94 respondents who belong to Generation Z in the city of Bhopal. The respondents are aged between 13 and 29 years and are becoming an active age group in financial decision-making in investment activities. The data were collected using a structured questionnaire, which was directed towards the behavioural, emotional and situational factors that affect investment behaviour. The sample was drawn using a non-probability sampling method, which was mainly convenience sampling, as it had an exploratory nature of the study and was accessible. The respondents were students, early-stage professionals or young respondents with different financial exposure and different levels of experience in investment. This diversity enabled researchers to get a wide-angle view of the emerging investment behaviours of Gen Z in the urban Indian context.

The sample size is not very large, but it is adequate for partial least squares structural equation modelling (PLS-SEM). The sample size is adequate for PLS-SEM, as per the "10-times rule" (Hair et al., 2011), which is used for this purpose. The sample size in the current study satisfies this requirement, thus ensuring the appropriateness of the data for the use of the structural model analysis.

3.2 Method of Analysis and Model

This study will use a multi-stage analysis of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Partial Least Squares Structural Equation Modelling (PLS-SEM) to analyse how the emerging emotional factors and situational factors affect the investment behaviour of Gen Z investors.

During the first phase, EFA was used to reveal the internal meaning of the observed variables and to look for new construct formation from the data set. Those with low factor loadings and high cross-loadings were deleted to ensure an interpretable and clear factor structure.

The second stage involved CFA and was used to validate the measurement model and to verify the factor structure obtained in the EFA stage. Cronbach's alpha and the composite reliability and average variance extracted (AVE) were used to check reliability and validity. The Fornell–Larcker criterion was employed for the discriminant validity.

In the last phase, to test the relationships between the constructs, PLS-SEM was applied with the software SmartPLS. PLS-SEM can be used in exploratory and prediction-oriented research and works well for relatively small samples (Hair et al., 2014). Fit of the structural model was tested with path coefficients, coefficient of determination (R^2) and predictive relevance (Q^2) and statistical significance of the relationships was tested with bootstrapping.

3.3 Variable justification

The variables in the study were identified and validated systematically by using factor analysis. Initially, Exploratory Factor Analysis (EFA) was used to determine the latent constructs that were assumed to be represented by the observed variables, since Exploratory Factor Analysis is seen as a suitable technique for grouping variables that are interrelated into meaningful factors (Hair et al., 2014). Two main independent factors and one dependent factor, Socially Driven Impulsive Investment (SDII), Financial Growth Engagement Factor (FGEF) and Investment Decision Behaviour (IDB), were derived based on factor loadings, conceptual relevance and retained variance. Following this, A Confirmatory Factor Analysis (CFA)

was carried out to confirm the reliability and validity of these constructs as suggested by Anderson and Gerbing (1988) and Hair et al. (2019). Once the measurement properties have been established to be satisfactory, validated constructs were added to the structural model to understand their impact on Investment Decision Behaviour (IDB) for Gen Z investors.

4. EMPIRICAL RESULTS

The empirical results of this study are presented using Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Partial Least Squares Structural Equation Modelling (PLS-SEM). First, some preliminary tests were conducted, such as the Kaiser—Meyer—Olkin (KMO) measure and Bartlett's Test of Sphericity, which proved that the data were adequate and suitable for the purpose of factor analysis. The EFA then revealed three factors, namely, Financial Growth Engagement Factor (FGEF), Socially Driven Impulsive Investment (SDII), and Investment Decision Behaviour (IDB), that had satisfactory factor loadings and an acceptable cumulative variance explained. Moreover, reliability and validity tests (CFA and PLS-SEM) showed good indicator reliability, internal consistency of the items, convergent validity and discriminant validity of the measurement model. Lastly, the results of the structural model showed that both FGEF and SDII positively develop Investment Decision Behaviour, wherein FGEF has a relatively strong influence. The model also demonstrated a good level of explanatory and predictive relevance, suggesting the appropriateness of the proposed framework in explaining investment decision behaviour of the respondents.

Table -1: Sampling Adequacy and Sphericity Test Results

Measure	Value
KMO Measure of Sampling Adequacy	0.790
Bartlett's Test of Sphericity (χ^2)	698
Bartlett's Test (df)	91
Bartlett's Test Sig. (p)	< .001

Source(s): Credit: Author computation

To make a measurement model reliable, some preliminary tests are essential, as shown in Table 1. To determine the sufficient relationship among indicators, Bartlett's Test of Sphericity was used ($\chi^2 = 698$, $df =$

91, $p < 0.001$), which is ideal and statistically significant. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was also tested and found to be 0.790, indicating a good level of adequacy in the sample and suggesting suitability and appropriateness for conducting Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and other further tests.

After achieving the criteria of the preliminary test, to determine the strength of the factor by analyzing how much variance is extracted by each factor, the eigenvalue is calculated and found to be 4.3215, explaining 22% of variance in factor 1, which indicates the highly influential and required factor, 1.8743 in factor 2 and 1.2159 in factor 3, explaining 19.1 and 18.1 respectively indicating the moderately influential but acceptable and above the threshold limit of >1 . Cumulatively, the total variance is 59.2%, which is considered acceptable for the retained factors.

Moving forward in factor structuring, it is essential to determine the relationship between an observed variable (indicators) and a latent factor, Factor Loadings are calculated to identify the strength and direction between the items and latent variable using Principal Axis Factoring with Oblimin rotation shows high loadings (ranging from 0.655 to 0.832) in Financial Growth Engagement Factor (FGEF) which indicates indicators are highly associated, correspondingly Factor 2 (ranging from 0.563 to 0.761) shows moderate to high loadings in Socially Driven Impulsive Investment (SDII) and Factor 3 (ranging from 0.661 to 0.855) shows high loadings in Investment decision behaviour which reflects suggests items are moderate to highly linked with the construct. Additionally, the uniqueness value of all items is below 0.50 except SDII 5 (slightly above), which is a good indicator that all the items have high communalities, and unexplained item variance is quite low. Overall, the measurement scale is good and appropriate, because of moderate-to-high factor loadings, high communalities between items and variables, low uniqueness, and no cross-loadings.

In Subsequent analysis for the measurement model, Factor loadings were assessed in PLS-SEM, in which all loadings are more than 0.50, as shown in Table IV. This is an acceptable value of Cronbach's Alpha values for Financial Growth Engagement Factor (FGEF) is 0.860, Investment Decision Behaviour (IDB) is 0.869, and Social Driven Impulsive Investment (SDII) is 0.827, respectively. Similarly, composite reliability values are calculated, in which ρ_A for all constructs are found above 0.70, which is above the threshold

limit. Further, Convergent validity is also tested by Average Variance Extracted (AVE) values for FGEF (0.640), IDB (0.707), and SDII (0.588), which demonstrate satisfactory levels of indicator reliability, internal consistency reliability and convergent validity across all factors.

Further, the results of Confirmatory Factor Analysis (CFA) calculated positive values of standardized estimates, lower standard errors (~ 0.08 – 0.14), high z values and statistically significant p - values ($p < 0.001$) also proved that the model has achieved an adequate and satisfactory level of indicator reliability and convergent validity.

Discriminant validity is tested and achieved by applying the Fornell-Larcker Criterion, in which the square root value of AVE for each factor is shown high diagonally (FGEF – 0.800, IDB – 0.841 and SDII – 0.767) in the respective column and in the corresponding row, as shown in Table 2, which indicates the higher variance among the constructs with their respective items and shows dissimilarity with other constructs. With some limitations of the Fornell-Larcker Criterion (like low sensitivity, heavy dependence on AVE, cross-loadings issue), the Heterotrait–Monotrait ratio (HTMT) in SEM is applied to check the discriminant validity and found all the values of HTMT < 0.85 , which is below the threshold limit, finally proving and suggesting that all the constructs are truly distinct from each other and maintain the dissimilarity among the constructs, and all values of VIF are also found below 3, indicating no multicollinearity issues among independent variables.

Table -2: Discriminant Validity

(Fornell- Larcker Criterion)

Source(s): Credit: Author computation

Variable	FGEF	IDB	SDII
Financial Growth Engagement Factor	0.800	-	-
Investment Decision Behaviour	0.454	0.841	-
Social Driven Impulsive Investment	0.218	0.363	0.767

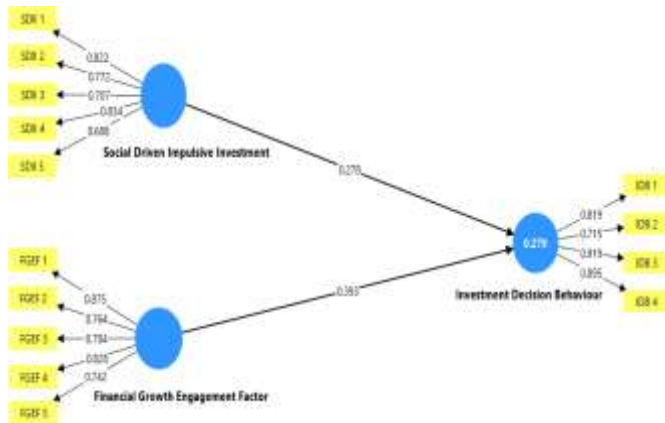


Fig -1: Measurement Model Assessment.

Source(s): Credit: Author's own creation

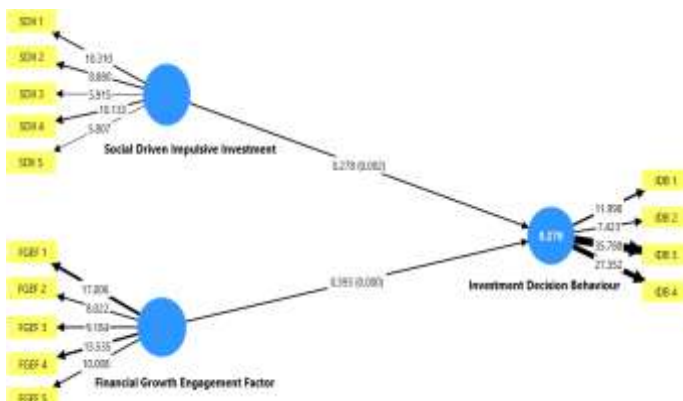


Fig -2: Structural Model Assessment.

Source(s): Credit: Author's own creation

After achieving Construct Reliability shown in Figure 1, which shows significant and adequate outer loadings in the outer model (Measurement Model), and to check the test of significance, bootstrapping results are used in which, t-values of all the constructs i.e. SDII, FGEF and IDB are calculated which found higher than 1.96 at 5% level of significance, confirming that all indicators significantly contribute to their respective constructs shown in Figure 2.

Thereafter, PLS – SEM is used to test the Inner Model (Structural Model) shown in Figure 2, in which the results indicate that both independent variable has a positive impact on dependent variable, that it shows moderating effect of Social Driven Impulsive Investment (SDII) on investment decision behaviour (IDB) i.e. ($\beta = 0.278$, $t = 3.098$, $p = 0.002$) reported in Table VIII which suggests socially driven impulsive behaviour has a limited contribution in influencing investment decisions. However, a strong effect is found in Financial Growth Engagement Factor (FGEF) on investment decision behaviour (IDB), i.e. ($\beta = 0.393$, $t = 4.753$, $p < 0.001$), which demonstrates that investment decision behaviour of investors is highly triggered who are highly engaged in financial knowledge, informed about financial investments and seek financial growth in the market. the relationship between FGEF and IDB is statistically significant ($\beta = 0.393$, $t = 4.753$ and $p < 0.001$), which means that the null hypothesis (H_1) is rejected.

Subsequently, the coefficient of determination (R^2) is calculated, i.e. 0.279, which highlights 27.9 % variance is explained by the independent variable, i.e. SDII and FGEF, and 72.1 % is unexplained variance, which might be due to other factors that are not studied in this model and measurement errors, which is a weak indication but a considerable explanatory power in behavioural research.

Apart from this, for determining the importance of the predictor variable, Effect size is calculated in which the FGEF shows a moderating effect size ($f^2 = 0.205$), which provides limited value as a contributing predictor in influencing investment decision behaviour, whereas SDII has a small effect size ($f^2 = 0.102$), indicating minor influence on IDB. Likewise, SDII and IDB have a significant relationship ($\beta = 0.278$; $t = 3.098$; $p = 0.002$); hence, there is rejection of the null hypothesis (H_2).

Table -3: Predictive Relevance

Indicator	Q ² Predict	PLS-SEM RMSE	LM RMSE	PLS-SEM MAE	LM MAE
IDB 1	0.01	1.05	1.094	0.818	0.869
IDB 2	-0.02	1.089	1.143	0.913	0.919
IDB 3	0.26	0.909	0.964	0.719	0.753
IDB 4	0.248	0.958	1.03	0.776	0.822

Source(s): Credit: Author computation

Furthermore, predictive relevance results are calculated using Q^2 , and error comparison measures are shown in Table 3, which revealed that IDB 3 (0.26) and IDB 4 (0.248) have moderate predictive indicators, whereas IDB 1(0.01) has a very small predictive relevance with no predictive ability in IDB 2 (-0.02).

In addition, in Table 3, the PLS-SEM model shows lower RMSE and MAE values compared to the linear

model (LM), which indicates lower prediction errors and better accuracy of the PLS- SEM model.

5. CONCLUSIONS

The present study was aimed at exploring the effect of Financial Growth Engagement Factor (FGEF) and Socially Driven Impulsive Investment (SDII) on Investment Decision Behaviour (IDB) of Gen Z investors through EFA, CFA and PLS-SEM methodologies. The empirical results showed that the measurement model showed sufficient internal consistency, convergent validity, and discriminant validity. The factor analytical results proved to be able to determine three significant factors with good factor loadings and cumulative variance.

Furthermore, the results of the analysis of the model showed that Financial Growth Engagement Factor (FGEF) and Socially Driven Impulsive Investment (SDII) had both a positive and significant effect on Investment Decision Behaviour of Gen Z investors. The two predictors showed a relatively stronger effect on investment decision behaviour, with FGEF showing a stronger effect, suggesting that investors who are financially growth-oriented and actively engaged in investing are more likely to play an effective role in investment activities. The effect of SDII was comparatively small but statistically significant, indicating that social influence, peer behaviour and impulsive tendencies also play a part in the investment decision-making process of Gen Z investors.

The model also exhibited good explanatory and predictive capability with R^2 , Q^2 predict, RMSE and MAE values, indicating that the proposed framework is suitable and has good prediction power in behavioural finance research. In conclusion, the results provide further evidence to the body of research on emerging behavioural and emotional factors influencing investment behaviour, specifically for Gen Z investors.

This research builds on the already rich body of Behavioural Finance literature and extends the scope of knowledge of investment behaviour beyond the scope of traditional behavioural biases. The study identifies new emotional and situational variables that are now impacting the investment choices of Gen Z investors. The study also adds to the scarce literature available on

the Indian context, especially young investors in Tier-II cities, such as Bhopal. From a methodological perspective, the application of EFA, CFA and PLS-SEM offers a holistic approach to study the modern constructs of behaviour in the investment decision-making process and can be used as a guideline for further research in behavioural finance.

6. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

The study has some limitations that have to be taken into account when interpreting the results. First, it is a geographically limited study with investors from Gen Z in Bhopal, so it may not be generalizable to other regions or demographic groups. Second, the primary data used were cross-sectional data obtained from self-reported questionnaires, which may have response bias and may not reflect changes in behaviours over time. Third, only the selected emerging emotional and situational factors were explored, while other behavioural, cultural, technological, and economic factors could have an impact on investment behaviour. Lastly, convenience and purposive sampling may result in a sample that is not representative. Further research can be longitudinal, involving a wider geographical scope and exploring further behavioural aspects to gain more insights into Gen Z investment behaviour.

REFERENCES

1. Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modelling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411–423.
2. Arora, J., & Gupta, P. (2026). Emotional investing in India: The importance of clear communication. *Review of Behavioural Finance*. <https://doi.org/10.1108/rbf-05-2025-0181>
3. Baker, H. K., Kumar, S., & Goyal, N. (2021). Emotional biases in investment decision-making: A behavioural finance perspective. *Journal of Behavioral Finance*.
4. Bikhchandani, S., & Sharma, S. (2001). Herd behavior in financial markets. *IMF Staff Papers*, 47(3), 279–310.
5. Chandra, A., & Kumar, R. (2012). Factors influencing Indian individual investor behaviour: Survey evidence. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2029642>

6. Dhar, R., & Zhu, N. (2006). Up close and personal: Investor sophistication and trading behaviour. *The Journal of Finance*, 61(2), 725–747.
7. Gupta, R., & Singh, A. (2022). Behavioural biases among retail investors in India. *Journal of Behavioral Finance*.
8. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.
9. Hii, I. S. H., & Ong, Y. X. (2025). Finfluencer: Can financial social media influencers promote desirable financial behaviours? *International Journal of Bank Marketing*.
<https://doi.org/10.1108/IJBM-05-2024-0256>
10. Housel, M. (2020). *The psychology of money*. Harriman House.
11. Kumar, S., Sharma, R., & Gupta, P. (2023). Impact of social media and psychological factors on investment behaviour of Gen Z investors. *Journal of Behavioral Finance*, 24(2), 150–165.
12. Mahmood, F., Arshad, R., Khan, S., Afzal, A., & Bashir, M. (2024). Impact of behavioral biases on investment decisions and the moderation effect of financial literacy: An evidence of Pakistan. *Acta Psychologica*, 247, 104303.
<https://doi.org/10.1016/j.actpsy.2024.104303>
13. Manzoor, A., Jan, A., & Shafi, M. (2023). Behavioral finance—An emerging theory: A review study. *Indian Journal of Research in Capital Markets*, 10(1), 34.
<https://doi.org/10.17010/ijrcm/2023/v10i1/172802>
14. Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91.
<https://doi.org/10.2307/2975974>
15. Nofsinger, J. R. (2017). *The psychology of investing* (6th ed.). Routledge.
16. Prendergast, G., Lee, C., & Wong, K. (2024). Gamification and digital nudges in retail trading platforms: Effects on investor behaviour. *Journal of Behavioral Finance*, 25(1), 45–60.
17. Raut, R. K., Das, N., & Kumar, R. (2018). Extending the theory of planned behaviour: Impact of past behavioural biases on the investment decision of Indian investors. *Asian Journal of Business and Accounting*, 11(1), 265–291.
18. Shah, B., & Butt, K. A. (2024). Heuristic biases and investment decision-making of stock market investors: A review paper. *Vision*.
<https://doi.org/10.1177/09722629231220985>
19. Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, 17(1), 83–104.
20. Statman, M. (2019). *Behavioral finance: The second generation*. CFA Institute Research Foundation.