The Clarion Volume 15 Number 1&2 (2026) PP 15-21
The Clarion
ISSN : 2277-1697
International Multidisciplinary Journal

Demographic Factors Shaping Risk Appetite in Retail Investment Decisions: A Behavioural Study in Assam.

Avisek Purkayastha and **Nilanjana Deb**
Assam Science and Technology University, Guwahati, India
Girijananda Chowdhury University, Guwahati, India.

Abstract

This study examined the demographic and experiential determinants of risk attitudes among 386 investors from Assam, using an 11-variable risk assessment instrument. Composite risk scores (range = 0 to 55, mean = 34.23, SD = 5.812) were categorised in low risk (below 28), moderate risk (28-40) and high-risk categories (above 40). After confirming normality, group comparisons were performed using ANOVA, independent t-test, and Bonferroni post hoc tests. Significant differences in mean risk scores were observed for age, marital status, employment and personal annual income. In contrast, no significant effects were found for education, gender, or family income, and correlations with household earning members. The findings suggest that risk appetite is shaped more by life stage than by formal education or simple household metrics, with implications for targeted investor education, product design, and regulatory safeguards.

Keywords : Risk appetite; Retail investors; Demographic factors; Risk perception, Behaviour Biases; Assam.

Introduction

The willingness and capacity of retail investors to accept market volatility and potential financial losses in pursuit of returns, defined as risk appetite, has emerged as a critical area of study in behavioural finance (Azad and Sharma, 2025). Risk appetite helps financial institutions in developing investment products and financial advisors in designing portfolios (Reddy et al., 2024). It can also help regulators in developing protection mechanisms.

Among the demographic factors, age is perhaps the most consistently documented predictor of risk appetite across cultures and measurement contexts. Duell et al. (2018), in their cross-national study across 11 countries, found that risk-taking propensity follows an inverted-U pattern, peaking in late adolescence and declining thereafter into early adulthood. The study suggested that the age–risk appetite relationship reflects both neurobiological maturation and life-stage transitions associated with reduced opportunity for certain risk behaviours. They also shed light on household composition, i.e. number of dependents and earning members. The study suggests that parental responsibilities and the need to secure household finances for dependent care constrain individuals' willingness to pursue risky financial strategies.

In terms of gender, the above study and another study by Bayar et al. (2020) found that gender was a significant predictor of financial risk tolerance in their Turkish university sample, with males more likely to be in higher-risk-tolerance categories than females. It was also found that educational level was a significant positive predictor of financial risk tolerance; individuals with postgraduate education were significantly more likely to pursue above-average or substantial financial risks than those with lower educational attainment. This study also showed a positive association between personal annual income and total family income and financial risk appetite.

Furthermore, marital status is increasingly recognised as a significant demographic predictor of risk appetite. Ansari and Bansal (2025) found that marital status was a significant predictor of financial risk tolerance, with married women showing different patterns of risk tolerance compared to single women across low, moderate, high, and above-average risk

Corresponding author : dr.nilanjanadeb2@gmail.com
DOI : 10.5958/2277-937X.2026.00001.0

categories. The same study also found that employment status and work experience were significantly related to financial risk tolerance, and employment security and accumulated work experience influence confidence in risk-bearing capacity.

The risk appetite of retail investors depends on several factors. Evidence suggests that investors' preference for returns over safety correlates with overconfidence bias and the underestimation of downside risk exposure (Azad and Sharma, 2025; Osman et al., 2025). The willingness of an investor to risk capital for higher returns and transition from loss domains to gain domains shows increased risk-seeking behaviour, which has been confirmed by the presence of highly volatile securities and speculative positions (Kahneman and Tversky, 1979; Kahneman and Tversky, 1982). Also, empirical studies on margin trading behaviour clearly show a connection between willingness to lose principal and using leverage (Iwatsubo and Rieger, 2024).

Investor preference for small-cap and mid-cap equities over large-cap securities reflects several distinct behavioural mechanisms. From a volatility perspective, smaller capitalisation securities exhibit significantly higher price momentum and absolute price movements, creating the illusion of superior return, and investors allocate large parts of their capital to such firms receiving media attention (Ahir and Prajapati, 2025). The avoidance of large-cap securities and exchange-traded funds due to their perceived "slow" price movements shows a disconnect between return expectations and time horizon. It also correlates with familiarity bias and home-based bias, where investors prefer concentrated positions in directly held individual securities over diversified indices which are perceived as less engaging (Nurcahya and Maharani, 2021). Empirical evidence, however, shows that large-cap diversified portfolios substantially outperform concentrated small-cap allocations on a risk-adjusted basis, especially during market dislocations (Kumar and Sabharwal, 2024). Although such portfolios face volatility higher than well-diversified alternatives, this reality fails to modify investor preferences, suggesting deep cognitive barriers to accepting diversification benefits (Liu, 2022).

In terms of stock selection, the adoption of technical analysis by retail investors persists despite decades of academic evidence questioning pattern predictability, as it yields mixed returns. Some chart patterns demonstrate modest predictive capacity under certain market conditions, but transaction costs and whipsaw effects nullify any statistically significant predictability when practical implementation is done (Ardiansyah, Nikmah and Irwandy, 2025). Comparative analysis of technical versus fundamental analysis suggests that investors utilising fundamental analysis identify superior return opportunities in emerging markets, yet technical analysis appeals predominantly to shorter-term oriented investors with limited financial literacy who perceive chart patterns as objective signals requiring less analytical effort than financial statement analysis (Logambal and Kanagasabapathy, 2024).

In terms of taking an entry into a position, periodic investment in fixed amounts, also known as dollar cost averaging (DCA), represents a paradox within behavioural finance. On average it is known to be suboptimal, yet it is considered rational as a strategy mitigating behavioural errors. Mathematical analysis demonstrates that DCA systematically underperforms lump-sum investing in rising markets, yet substantially outperforms in declining markets when psychological loss aversion triggers panic selling (Kirkby et al., 2020). However, DCA approaches with frequency adjustment in response to market conditions deliver superior outcomes to both constant DCA and lump-sum strategies (Lin and Xu, 2016).

The role of news and media in stock purchasing preferences reflects attention-driven investing, and information overload reduces the quality of investment decisions. Investors receiving excessive information show greater susceptibility to sentiment-driven trading (Shantha Gowri and Ram, 2019). Social media amplifies news-driven investment bias through multiple mechanisms. Rapid information dissemination increases recency bias, peer commentary increases herding tendency, and gamification elements reinforce overconfidence (Awad et al., 2025). Good news produces underreactions and delayed price adjustments, whereas bad news triggers sharp corrections. This asymmetry suggests that investor attention is influenced more by the emotional impact of information than by its content (Xu et al., 2023).

Momentum investing reflects investors' tendency to extend recent price trends to expectations of future returns. This behavior illustrates the extrapolation bias and reliance on trend-following heuristics, where momentum signals are given more weight than mean reversion patterns (Chaudhary et al., 2025). These strategies often show profitability in empirical tests, indicating that price movements may carry predictive signals. However, these profits tend to diminish when retail investors heavily adopt momentum trades, leading to crowded positions in the market. From a behavioural perspective, this pattern can be explained by the disposition effect, where investors hold onto winning stocks longer than fundamentals justify, and loss aversion, where losing stocks are sold quickly. Together, these biases generate price trends that support momentum strategies until excessive crowding causes reversals (Alanazi and Alanazi, 2020).

However, even though investors who engage in fundamental analysis are influenced by several biases, such as confirmation bias, where financial data are interpreted to support existing views; anchoring, where initial valuation estimates are relied on too heavily; and representativeness, where companies are judged based on stereotypical patterns in their metrics (Cui, 2024), engaging in fundamental analysis is a strong behavioral predictor of investment success and effective risk management. Empirical studies have shown a significant positive link between the practice of fundamental analysis and higher investment returns, especially among financially literate retail investors (Seng and Hancock, 2012).

From a risk management perspective, borrowing capital for investment is a clear sign of overconfidence and speculative behaviour among retail investors. Behavioural finance theory suggests that leverage magnifies existing biases: overconfident investors become even more overconfident, loss-averse investors take on greater risks, and herding tendencies grow stronger (Zhang, 2023). Overconfident investors open margin positions, and subsequent losses often lead to panic-driven increases in leverage, reflecting the gambler's fallacy and escalation of commitment, which further deepens losses (Singh, Malik and Jha, 2024). Studies across different markets show that margin traders earn lower risk-adjusted returns, face consistent losses from margin calls, and are more exposed to portfolio collapses during market shocks (Jain, 2025).

Objective of the Study

This study attempts to examine the influence of demographic factors on shaping risk appetite in retail investment decisions.

Research Methodology

This study employed snowball sampling, a non-probability sampling technique, to recruit respondents. Snowball sampling is beneficial when the target population is difficult to directly access. It begins with a small group of individuals who meet the inclusion criteria, and expands by asking them to refer to others within their network who also qualifies. The initial participants were identified through personal contacts. The individuals were then asked to complete a structured questionnaire and were invited to refer to others in their social network who might be interested and eligible to participate. This referral process continued until saturation was reached. Data were collected using a self-administered structured questionnaire with a five-point Likert scale introduced against most of the questions in the questionnaire.

Furthermore, from the reviewed literature, 11 (eleven) variables were identified that could possibly shape the risk appetite of retail investors in Assam. The variables are tabulated and discussed in detail below. ANOVA, t-test, and Pearson's correlation were used to identify the various demographic variables that shaped the risk appetite of retail investors in Assam.

This study helps identify behavioral patterns in investment decision-making that emerge from these demographic differences and provides insights into how demographic diversity shapes behavioral biases and investment strategies among retail investors. This may help policymakers and financial institutions design investor education programs, risk management tools, and tailored financial products for different demographic groups.

The factors (VR1 to VR11) are as follows:

VR1	Returns are more important than safety
VR2	I'm willing to risk losing principal for higher return
VR3	I prefer to invest more in small and mid-cap stocks
VR4	I avoid large cap stocks and ETFs because price movements are slower within one year
VR5	I believe highly diversified portfolio of stocks might give less returns
VR6	I prefer buying stocks on the basis of chart patterns (Technical Analysis)
VR7	If I want to buy a number of shares (say 50), I prefer to buy them over a period of time (5 shares each in 10 different days) rather than buying at once
VR8	I prefer buying stocks that has been in the news
VR9	I prefer buying/selling stocks that has recently shown above average price movement
VR10	VR10 - Before investing in a company I study the financials (Fundamental analysis)
VR11	I'm willing to borrow money to invest if probability of possible returns is high

Analysis and Interpretation

Weights were assigned to each variable, and the total risk score was calculated based on the responses.

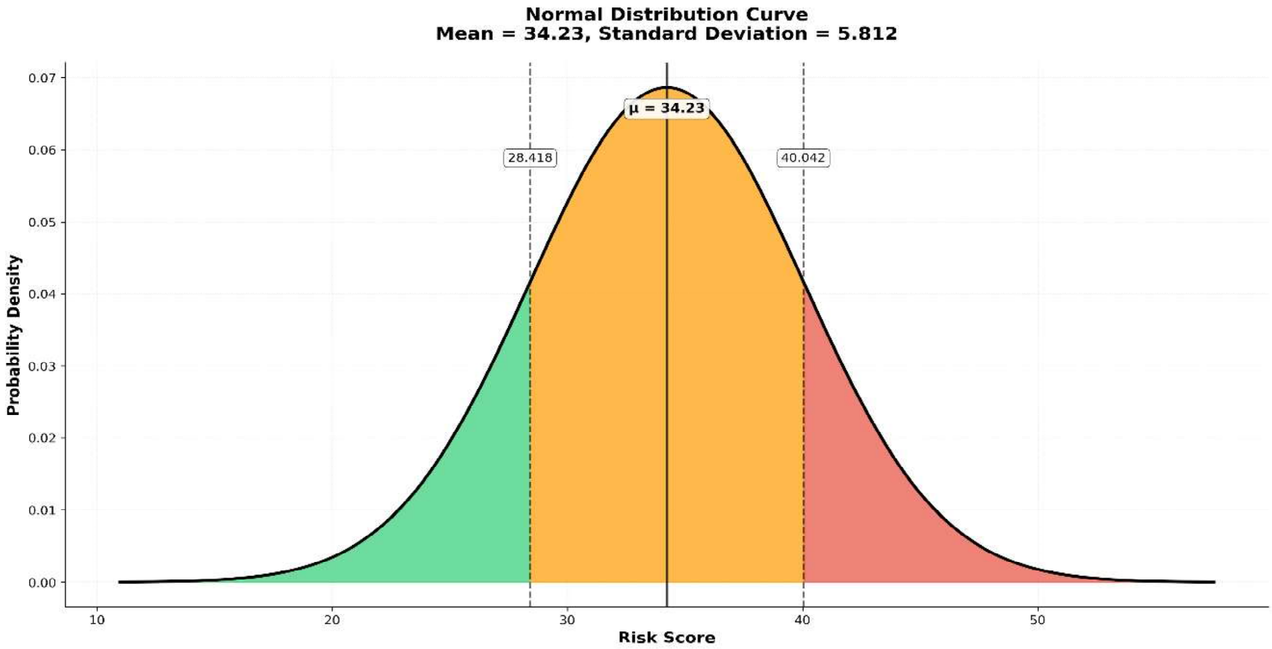
Normality Test (Risk Scores)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
TotalRiskScore	386	19	49	34.23	5.812	33.780
Valid N (listwise)	386					

Shapiro Wilk test with p-value > 0.05 and the histogram suggests normality. We ignore the Kolmogorov Smirnoff test as it is sensitive to large samples *(n=386)* and may detect small deviations from normality as significant. In addition, the distribution of the scores demonstrated excellent symmetry with a skewness coefficient of -0.006, indicating perfect symmetry around the mean, which was also confirmed by the histogram.

Using the data, we set the parameters as moderate risk in the first standard deviation around mean i.e. 34.23±5.81 which is 40.04 and 28.41. We approximated the range as between 28 and 40(n=282). Participants scoring less than 28 were defined as low-risk takers (n= 50), and participants scoring more than 40 were defined as high-risk takers (n=54).



Within the high-risk takers(n=54), 44 were male and 10 were female, 40 were in the age group 18-32, 39 were unmarried, and 35 had two or fewer dependents in their family. In this group, we can conclude that the high-risk-taker group profile is predominantly young, male, unmarried, and with relatively few dependents, suggesting that higher risk-taking is concentrated among individuals with fewer immediate family responsibilities and earlier life course commitments.

Within the low-risk group (n=50), 35 were male and 15 were female, 33 were above the age of 32, 31 were married, and 35 had less than two dependents in their family. Hence, we conclude that respondents classified as low-risk takers were mostly male, above 32 years of age, married, and had fewer than two dependents, suggesting that lower risk tolerance is more prevalent among older, married individuals with family responsibilities.

Risk Scores Vs Demography

Demographic Variable	Alternative Hypothesis	Test Conducted	P-Value
Age	H_1: Difference in risk scores according to age exists	ANOVA	0.000
Education	H_2: Difference in risk scores according to educational background exists	ANOVA	0.602
Gender	H_3: Difference in risk scores according to gender exists.	Independent T Test	0.548
Marital Status	H_4: Difference in risk score exists according to marital status.	Independent T Test	
Employment	H_5: Difference in risk scores according to employment exists.	ANOVA	0.000
Annual Income	H_6: Difference in risk scores according to annual income exists.	ANOVA	0.000 0.001
Family Income	H_7: Difference in risk scores according to family income exists.	ANOVA	0.202

For the last two demographic factors, i.e. number of earning members and number of dependents, which are both continuous data along with risk scores, Pearson's Coefficient of Correlation was carried out. We see weak inverse correlation (r = -0.070) between earning members and risk scores, indicating a very weak inverse relationship. As the number of earning members increases, risk scores tend to decrease slightly. However, the strength of this relationship is negligible, suggesting that the number of earning members does not meaningfully influence the risk appetite. Between dependents and risk scores, we again see a weak direct correlation (r = 0.097). As the number of dependents increases, risk scores rise slightly; however, the relationship is weak, indicating that dependents have little practical impact on risk appetite.

Results and Discussion

Risk Categories

The composite risk score, derived from the summation of responses across 11 investor risk attitude variables (VR1-VR11), demonstrated a mean of 34.23 (SD = 5.812) across the 386 respondents. After confirming approximate normality using the Shapiro-Wilk test (p = 0.076), minimum deviation from normality and near-symmetry, with a skewness value of "0.006 and kurtosis of "0.16,9 and a large sample size, parametric analyses (ANOVA and independent sample t-tests) were deemed appropriate, as these tests are robust to minor violations of normality for n > 30. Respondents were subsequently classified into three risk categories based on the standard deviation boundaries: low risk (score < 28.42), moderate risk (score 28.42–40.04), and high risk (score > 40.04).

Inferential analyses

One-way ANOVA and independent t-tests were used to compare mean risk scores across demographic and portfolio groups. The key findings are summarized below.

- Age (18–32 years, 33–46 years, 47–60 years, >60years): ANOVA was significant. Post hoc comparisons indicated that the 18–32 group differed significantly from the 47–60 and >60 groups, with younger respondents exhibiting higher risk scores than older cohorts.
- Education (Undergraduate, Graduate, Postgraduate, PhD): ANOVA not significant; no evidence that formal education level affects the composite risk score.
- Gender (Male, Female): independent t test not significant; no gender difference in risk score.
- Marital status (Married, Unmarried): independent t-test significant; marital status is associated with different mean risk scores.
- Employment (student, service, self employed, retired, homemaker): ANOVA was significant. Students and salaried (service) respondents differed significantly; other pairwise contrasts

were not significant.

- Personal annual income (below 5 Lakhs, 5–10 Lakhs, 10–15 Lakhs, 15–20 Lakhs, above 20 Lakhs): ANOVA significant. The below 5 lakh group differed significantly from the 10–15 Lakh and 15–20 Lakh groups; other pairwise contrasts were not significant.
- Family income (below 8, 8–15, 15–25, above 25): ANOVA not significant; no association with the risk score.
- Household composition: Pearson correlations show the number of earning members vs. risk score (r = " 0.070) and dependents vs. risk score (r = 0.097). Both correlations were extremely weak and practically negligible.

The composite risk score centers were in the moderate range (mean = 34.23). Significant differences in risk appetite were associated with age, marital status, employment category, and personal income. On the other hand, education level, gender, family income, and simple household composition measures showed little or no meaningful relationship with the risk score.

Interpretation in Behavioral Terms

- **Age and life stage:** Younger investors (18–32 years) displayed higher risk scores than older cohorts (47–60 and >60 years). This pattern aligns with behavioral finance evidence that younger investors tolerate greater volatility, may be more prone to speculative strategies, and are more active on digital trading platforms than older investors.
- **Employment and income effects**: Significant differences between students and salaried workers, and between the lowest personal income group and middle-income groups, indicate that financial capacity and life circumstances influence risk preferences. Students may accept higher risk due to longer investment horizons or lower opportunity costs, while low personal income respondents differ from middle earners in ways that could reflect necessity-driven choices.

Conclusion

The study confirms moderate overall risk tolerance among respondents, with significant demographic influence. Age, marital status, employment, and personal income emerged as key determinants of risk attitudes, whereas education, gender, family income, and household composition showed negligible effects. These findings underscore the behavioral relevance of life stage and financial capacity in shaping investment-risk preferences.

References

Azad, P. and Sharma, D.M., 2025. A review of behavioral biases and their impact on portfolio performance: An insight from retail investor in India's Nifty 50 segment. *International Journal of Accounting and Economics Studies*, 12(7), pp.203–207.

Reddy, S.P., Sharma, A. and Banerjee, D., 2024. Risk appetite and hedging strategies: The impact of age cohorts in financial markets. *Global Journal of Financial Markets and Investments*, 12(3), pp.234–256.

Duell, N., Steinberg, L., Icenogle, G., Chein, J., Chaudhary, N., Di Giunta, L., Dodge, K.A., Fanti, K.A., Lansford, J.E., Oburu, P. and Pastorelli, C., 2018. Age patterns in risk taking across the world. *Journal of Youth and Adolescence*, 47(5), pp.1052–1072.

Bayar, Y., Sezgin, H.F., Öztürk, Ö.F. and Şaşmaz, M.Ü., 2020. Financial literacy and financial risk tolerance of individual investors: Multinomial logistic regression approach. *Sage Open*, 10(3), p.2158244020945717.

Ansari, Y. and Bansal, R., 2025. Evaluation of demographic variables and their impact on financial risk tolerance among women. *Risk Governance & Control: Financial Markets & Institutions*, 15(3).

Kahneman, D. and Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), pp.263–291.

Kahneman, D. and Tversky, A., 1982. The psychology of preferences. *Scientific American*, 246(1), pp.160–173.

Iwatsubo, K. and Rieger, M.O., 2024. The key to succeed in FX margin trading: The role of investment strategy and behavioural biases. *SSRN*, 4822759.

Ahir, D.M. and Prajapati, C.A., 2025. Analyzing market capitalization trends of large-cap, mid-cap, and small-cap companies in India (2020–2024): A comparative study. *Vidhyayana*, 10(si3), pp.1470–1484.

Nurcahya, S.A. and Maharani, S.N., 2021. Investor competence and decision familiarity bias analysis for portfolio diversification. In: *ICONEBS 2020: Proceedings of the First International Conference on Economics, Business and Social Humanities*, November 4–5, Madiun, Indonesia. European Alliance for Innovation, p.271.

Kumar, S. and Sabharwal, A., 2024. An evaluation of large cap, mid cap, and small cap mutual funds: Return, risk, and investor considerations. *International Journal of Banking, Risk & Insurance*.

Liu, Y., 2022. Will and power: Investment diversification and systemic deviation from irrational risk. *Cogent Economics & Finance*, 10(1), p.2129367.

Ardiansyah, F.D., Nikmah, C. and Irwandy, M.H.B.A., 2025. Can technical analysis indicators predict future stock prices? Evidence from Elliot Wave and Fibonacci retracement.

Logambal, R. and Kanagasabapathy, G., 2024. Investment decision using technical analysis: A study on selected stocks in Indian stock market. *Shanlax International Journal of Economics*, 12(2), pp.62–68.

Kirkby, J.L., Mitra, S. and Nguyen, D., 2020. An analysis of dollar cost averaging and market timing investment strategies. *European Journal of Operational Research*, 286(3), pp.1168–1186.

Lin, E. and Xu, H., 2016. Modified dollar cost averaging investment strategy: Evidence from major developed international stock markets. *Journal of Finance Issues*, 15(1), pp.20–30.

Shantha Gowri, B. and Ram, V.S., 2019. Influence of news on rational decision making by financial market investors. *Investment Management and Financial Innovations*, 16(3), pp.142–156.

Awad, A., Aziz, A.F. and Shma, T.R., 2025. Investment behavior in the Egyptian stock market: The impact of social media on investor decision-making. *Investment Management & Financial Innovations*, 22(1), p.203.

Xu, L., Zhang, X. and Zhao, J., 2023. Limited investor attention and biased reactions to information: Evidence from the COVID-19 pandemic. *Journal of Financial Markets*, 62, p.100757.

Chaudhary, M.K., Adhikari, M., Ghimire, D.M. and Bhattarai, D.R., 2025. Heuristic bias and investment decision: Exploring the mediating role of investors' risk perceptions. *Investment Management & Financial Innovations*, 22(1), p.441.

Alanazi, A.S. and Alanazi, A.S., 2020. The profitability of technical analysis: Evidence from the piercing line and dark cloud cover patterns in the forex market. *Cogent Economics & Finance*, 8(1), p.1768648.

Cui, J., 2024. Behavioral finance: The impact of investor expectation on financial decision-making. *Advances in Economics, Management and Political Sciences*, 79(1), pp.39–43.

Seng, D. and Hancock, J.R., 2012. Fundamental analysis and the prediction of earnings. *International Journal of Business and Management*, 7(3), p.32.

Zhang, Y., 2023. The impact of investors' overconfidence bias on investment strategy based on behavioral finance. *Advances in Economics, Management and Political Sciences*, 8(1), pp.114–119.

Singh, D., Malik, G. and Jha, A., 2024. Overconfidence bias among retail investors: A systematic review and future research directions. *Investment Management & Financial Innovations*, 21(1), p.302.

Jain, A.K., 2025. Margin trading in India: A study of financial leverage, operational mechanisms, risks and regulatory compliance. *IJAIDR – Journal of Advances in Developmental Research*, 16(2).