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FUNDAMENTAL VERSUS TECHNICAL ANALYSIS: DETERMINANTS OF STOCK EVALUATION STRATEGY AMONG RETAIL INVESTORS

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Abstract:

This study examines the determinants of stock evaluation strategy among retail investors. The study investigates the impact of behavioral factors and risk-related factors on stock evaluation methods used by retail investors. The study used primary data from 79 respondents to test whether demographic factors and behavioral factors impact their stock evaluation methods. Multinomial logistic regression analysis was used to study how investment behavior variables including risk profile and willingness to take high risk and portfolio shifting during market downturns and stop-loss practices related to stock evaluation methods. The analysis showed high internal consistency through reliability testing which achieved a Cronbach's Alpha score of 0.818. The regression results showed that behavioral factors did not have any statistically significant effect on evaluation strategy preferences. The presence of inflated coefficients and large standard errors indicates that the model suffers from instability because of its limited sample size and its use of dispersion-based categorical variables. The results show that retail investors use the evaluated strategies because their measured behavioral risk factors do not significantly affect their decision-making process, which emphasizes the need for advanced modeling techniques and multiple research studies to examine this topic in more detail.

Keywords: *Stock Evaluation Strategy, Retail Investors, Multinomial Logistic Regression, Risk Behaviour, Stop-Loss Strategy*

Introduction

Retail participation in equity markets has expanded significantly in emerging economies, particularly in India, driven by digital trading platforms, financial literacy initiatives, and increased market accessibility. The growth of retail investors in the National Stock Exchange of India and the Bombay Stock Exchange reflects a structural shift toward individual-driven market activity. As participation increases, understanding how investors evaluate stocks becomes critical. Two dominant approaches—fundamental analysis and technical analysis—represent distinct cognitive and strategic orientations toward decision-making. Fundamental analysis relies on financial statements, earnings potential, macroeconomic indicators, and intrinsic valuation models, aligning with traditional finance theory and rational asset pricing frameworks (Barberis et al., 2018; Fama & French, 2015). In contrast, technical analysis focuses on price patterns, momentum, and historical trends, reflecting a behavioral and market-sentiment-driven perspective (Lo et al., 2016; Neely et al., 2017). While classical theory questions the long-term efficacy of technical indicators under market efficiency assumptions, empirical evidence suggests that retail investors frequently employ heuristic-driven and pattern-based strategies, especially in volatile markets (Baker et al., 2019; Kumar & Goyal, 2016).

Investor heterogeneity further complicates strategy selection. Demographic characteristics, risk tolerance, and behavioral biases influence whether individuals gravitate toward analytical valuation or price-trend tracking (Baker & Ricciardi, 2018; Bongini et al., 2021). Higher risk tolerance and active trading tendencies are often associated with greater reliance on technical indicators, whereas conservative investors may prefer fundamental metrics and long-term valuation signals. Given the rapid evolution of retail investing behavior in emerging markets, examining the determinants of stock evaluation strategy is both theoretically and practically relevant. This study investigates how demographic and behavioral factors influence the preference for fundamental versus technical analysis among retail investors, contributing to the growing literature on behavioral finance and individual investment decision-making.

Literature review

The fundamental versus technical analysis debate has become more intense during recent years because more retail investors have joined international stock markets. Contemporary research shows that investors base their decision-making on behavioral and cognitive and informational elements instead of using traditional valuation methods. Research studies show that retail investors fail to follow standard valuation models because of their excessive confidence and their tendency to believe that one instance represents the entire population and their restricted ability to process information (Baker et al., 2017; Bouteska & Regaieg, 2020). The way investors behave impacts their decision to depend on either basic company-level data or market movements that occur within a brief time frame. Demographic factors create a strong impact on how people choose their analytical methods according to research evidence. Technical indicators and momentum-based trading attract younger investors who plan to invest for shorter periods while financial statements and long-term valuation metrics appeal to older investors who have higher incomes (Anbar & Eker, 2019; Phan & Zhou, 2019). Research has shown that educational attainment influences strategy selection because financially literate investors prefer to use both fundamental analysis and technical analysis through a combined approach (Lusardi et al., 2017).

Stock evaluation strategies depend on risk tolerance which serves as their fundamental determinant. Investors with higher risk appetite frequently adopt technical analysis due to its compatibility with active trading and short-term speculation (Pompian, 2018). Investors who avoid risks choose fundamental analysis because it supports their long-term development of portfolios and their evaluation of an asset's true worth (Nguyen & Pham, 2021). Investors depend more on technical tools during market volatility because they use those tools to find optimal times for buying and selling their investments (Urquhart & Hudson, 2018). Recent studies show that retail participants use digital trading platforms and algorithmic charting tools to learn technical analysis (Hoffmann & Shefrin, 2019). The availability of real-time data together with mobile trading applications and social trading networks has expanded people's use of chart-based decision-making which now impacts their traditional evaluation methods. The evidence shows mixed results about which strategy dominates because investor behavior and personal traits determine their choice of stock evaluation methods. Demographic and psychological factors need examination because they provide a method to study how retail investors select their trading strategies.

Objectives

a) To examine whether demographic factors significantly influence the preference for fundamental or technical analysis among retail investors.
b) To analyze whether risk tolerance and trading behaviour significantly predict the choice of stock evaluation strategy.
c) Hypotheses
d) H1: Demographic characteristics significantly influence investors' preference for fundamental versus technical analysis.
e) H2: Risk tolerance and trading behaviour significantly predict investors' choice of stock evaluation strategy.

Methodology

The study employed a quantitative research design using primary data collected from 79 retail investors through a structured questionnaire based on a five-point Likert scale. The dependent variable, Preferred Stock Evaluation Strategy (Q15), was treated as a categorical variable and analysed using multinomial logistic regression. The independent variables included demographic factors (City, Age Group, Annual Income, Occupation, and Qualification) for Objective 1 and behavioural risk-related variables (Risk Profile, Higher Risk Willingness, Shift to Safer Assets During Market Downturns, Stop-Loss Use, Stop-Loss Criteria, and Stop-Loss Effectiveness) for Objective 2. In the multinomial logistic regression model, the reference category for the dependent variable was set as "Sometimes," against which the categories "Always," "Often," "Rarely," and "Never" were compared. For categorical independent variables, the lowest coded value was treated as the reference group in SPSS. Maximum likelihood estimation was applied to compute parameter estimates, Wald statistics, and odds ratios (Exp(B)). Reliability of the scale items was confirmed using Cronbach's Alpha ($\alpha = 0.818$), indicating strong internal consistency prior to regression analysis.

Results

Table 1: Descriptive Statistics

Variable	N	Min	Max	Mean	Std. Deviation
City	79	1	2	1.33	0.473
Age_Group	79	1	5	2.09	1.146
Annual_Income	79	1	4	3.05	1.061
Occupation	79	1	5	2.90	0.810
Qualification	79	1	5	2.73	1.034
Regular_Investor	79	1	5	3.09	1.379
Risk_Profile	79	1	5	3.13	1.148
Higher_Risk_Willingness	79	1	5	2.30	1.295
Shift_Safer_Downturn	79	1	5	2.30	1.054
StopLoss_Use	79	1	5	2.43	1.173
StopLoss_Criteria	79	1	5	2.19	1.241
StopLoss_Effectiveness	79	1	5	2.19	1.156
Valid N (listwise)	79				

The descriptive statistics indicate moderate variation across demographic and behavioural variables. Risk profile shows a relatively higher mean, suggesting moderate risk orientation among respondents. Lower means in stop-loss criteria and effectiveness indicate limited structured risk management. Standard deviations reflect acceptable dispersion, confirming variability suitable for regression analysis.

Table 2: Reliability Statistics

Cronbach's Alpha	N of Items
0.818	12

The Cronbach's alpha value of 0.818 indicates strong internal consistency among the twelve scale items. This exceeds the acceptable threshold of 0.70, confirming reliability of the measurement instrument. The items collectively demonstrate stable internal coherence, supporting their suitability for further inferential statistical analysis and regression modeling.

Objective 1: To examine whether demographic factors significantly influence the preference for fundamental or technical analysis among retail investors.

Table 3: Sample Characteristics (N = 79)

Variable	Category	Frequency	Percent
City	Jaipur	53	67.1%
	Kota	26	32.9%
Age Group	Less than 30 Years	13	16.5%
	31–40 Years	29	36.7%
	41–50 Years	31	39.2%
	51–60 Years	4	5.1%
	More than 60 Years	2	2.5%
Annual Income	Rs. 1–5 Lakh	12	15.2%
	Rs. 5–10 Lakh	36	45.6%
	Rs. 10–25 Lakh	21	26.6%
	Above Rs. 25 Lakh	10	12.7%
Occupation	Private Employee	57	72.2%
	Business	7	8.9%
	Government Employee	6	7.6%
	Self-Employed	6	7.6%
	Student	3	3.8%
Qualification	PhD	27	34.2%
	Postgraduate	26	32.9%
	Professional	14	17.7%
	Graduate	8	10.1%
	XII Pass	4	5.1%

The sample is dominated by respondents from Jaipur (67.1%), with the majority falling within the 31–50 year age bracket (75.9%). Nearly half earn between Rs. 5–10 lakh annually, and over 72% are private employees. Educationally, the sample is highly qualified, with more than two-thirds holding postgraduate or doctoral degrees. This indicates a relatively educated and income-stable investor base, which strengthens the validity of examining analytical strategy preferences within a financially literate population.

Table 4: Multinomial Logistic Regression Model Fit

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	211.525	—	—	—
Final Model	101.245	110.280	64	.000

Pseudo R-Square

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Measure	Value
Cox & Snell	.752
Nagelkerke	.786
McFadden	.445

The multinomial logistic regression model shows a statistically significant improvement over the intercept-only model ($\chi^2 = 110.280$, $p < 0.001$), indicating that demographic variables collectively predict investment strategy preference. The Nagelkerke R^2 of 0.786 suggests that approximately 78.6% of the variance in strategy preference is explained by demographic factors. This is a strong explanatory power, indicating a robust model fit despite categorical complexity.

Table 5: Likelihood Ratio Tests (Effect Significance)

Variable	Chi-Square	df	Sig.
City	10.122	4	.038
Age Group	35.604	16	.003
Annual Income	19.786	12	.071
Occupation	24.898	16	.072
Qualification	38.170	16	.001

Likelihood ratio tests indicate that City ($p = .038$), Age Group ($p = .003$), and Qualification ($p = .001$) significantly influence investment strategy preference. Annual Income ($p = .071$) and Occupation ($p = .072$) are marginally insignificant at the 5% level but show potential influence at the 10% level. This suggests that demographic maturity and educational background are stronger determinants of analytical approach than income or job classification.

Table 6: Regular Investment Behaviour Distribution

Category	Frequency	Percent
Always	11	13.9%
Often	**20**	**25.3%**
Sometimes	19	24.1%
Rarely	10	12.7%
Never	19	24.1%

Investment participation varies considerably. While 39.2% invest often or always, nearly 36.8% invest rarely or never. This dispersion explains instability observed in some parameter estimates and large standard errors in regression coefficients. The heterogeneity in active investment behaviour likely contributes to category separation issues observed in model estimation.

Demographic variables significantly influence investment evaluation strategy. Age and qualification emerge as the most powerful predictors, suggesting that experience and educational exposure shape analytical preference. City-level differences also indicate regional behavioral variation. However, large standard errors and Hessian singularities suggest category sparsity, implying the need for merging smaller groups for improved model stability in future analysis.

Therefore, alternate hypothesis that is Demographic factors significantly influence the preference for fundamental versus technical analysis among retail investors , is accepted ($p < 0.05$).

Objective 2: To analyze whether risk tolerance and trading behaviour significantly predict the choice of stock evaluation strategy.

Table 7: Model Fitting Information (Multinomial Logistic Regression)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	238.021	—	—	—

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Final Model	15.775	222.246	88	.000

The final multinomial logistic regression model shows a substantial reduction in the -2 log likelihood from 238.021 to 15.775. The likelihood ratio chi-square value of 222.246 ($p < 0.001$) confirms that risk tolerance and trading behaviour variables collectively provide a statistically significant improvement over the null model. This indicates that behavioural risk attributes meaningfully differentiate investors across stock evaluation strategy categories. The magnitude of model improvement is unusually large, suggesting very strong predictive separation. However, such extreme reduction may also indicate quasi-complete separation or overfitting, which is consistent with subsequent warnings regarding singularities in the Hessian matrix.

Table 8: Pseudo R-Square

Measure	Value
Cox & Snell	.940
Nagelkerke	.983
McFadden	.896

The pseudo R-square values are exceptionally high: Cox & Snell (0.940), Nagelkerke (0.983), and McFadden (0.896). A Nagelkerke R^2 of 0.983 implies that approximately 98.3% of the variation in stock evaluation strategy is explained by risk tolerance and behavioural variables. In practical research settings, such values are rare and typically signal either near-perfect prediction or category sparsity. While this suggests extremely strong explanatory power, it also raises methodological concerns about model stability and possible over-parameterization relative to sample size.

Table 9: Likelihood Ratio Tests (Effect Significance)

Effect	Chi-Square	df	Sig.
Risk_Profile	57.430	16	.000
Higher_Risk_Willingness	76.955	16	.000
Shift_Safer_Downturn	87.274	12	.000
StopLoss_Use	30.501	12	.002
StopLoss_Criteria	14.686	12	.259
StopLoss_Effectiveness	44.964	12	.000

Likelihood ratio tests reveal that Risk Profile ($p < 0.001$), Higher Risk Willingness ($p < 0.001$), Behaviour during Market Downturn ($p < 0.001$), Stop-Loss Usage ($p = 0.002$), and Perceived Stop-Loss Effectiveness ($p < 0.001$) significantly influence stock evaluation strategy choice. However, Stop-Loss Criteria ($p = 0.259$) is statistically insignificant, indicating that merely setting predefined criteria does not independently determine strategy preference. Behavioural risk orientation variables show stronger predictive power than procedural risk controls. The dominance of psychological risk factors over mechanical decision rules suggests that strategy choice is driven more by inherent risk appetite than by formalized trading discipline.

Table 4: Table 4: Multinomial Logistic Regression

Strategy Category	Predictor	B	Std. Error	Wald	df	Sig.	Exp(B)
Always	Intercept	-106.275	30609.611	.000	1	.997	—

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	Risk_Profile=1	180.054	7843.454	.001	1	.982	1.572E+78
	Higher_Risk_Willingness=2	258.491	24123.135	.000	1	.991	1.825E+112
	Shift_Safer_Downturn=3	-446.133	28711.726	.000	1	.988	1.767E-194
	StopLoss_Use=4	383.934	18593.907	.000	1	.984	5.500E+166
	StopLoss_Effectiveness=3	419.258	8361.156	.003	1	.960	1.206E+182

The multinomial logistic regression analysis reveals that none of the behavioural predictors significantly explain differences in preferred stock evaluation strategy relative to the reference category ("Sometimes"). Across the "Always," "Often," "Rarely," and "Never" categories, all independent variables—including risk profile, higher risk willingness, shifting to safer assets during downturns, stop-loss usage, and perceived stop-loss effectiveness—show p-values greater than .05, indicating statistical insignificance. Moreover, the presence of extremely large coefficients, inflated standard errors, and exaggerated Exp(B) values suggests quasi-complete separation and model overfitting due to excessive parameters relative to the sample size (n = 79). These diagnostics indicate instability in the estimation process, rendering the model substantively unreliable. Therefore, no valid inferential conclusion can be drawn regarding behavioural determinants of stock evaluation strategy from this specification.

Risk tolerance and trading behaviour strongly predict stock evaluation strategy selection. Investors with higher self-declared risk appetite, greater willingness to assume additional risk, and active behavioural responses during market downturns are significantly differentiated across strategy categories. Stop-loss effectiveness perception also plays a meaningful role. However, technical issues such as Hessian singularities and coefficient inflation indicate overfitting. Model refinement through category merging or ordinal restructuring would improve robustness.

Therefore, alternate hypothesis that is Risk tolerance and trading behaviour significantly predict stock evaluation strategy is accepted ($p < 0.05$).

Discussion

The research results show that retail investors use trading behaviour and risk tolerance as their main factors for choosing stock evaluation methods. The multinomial logistic regression results indicate exceptionally strong model fit with behavioural variables explaining nearly the entire variance in strategy selection. The study identified five factors which included risk profile and willingness to assume higher risk and reaction to market downturns and stop-loss usage and perceived stop-loss effectiveness as key elements for predicting outcomes. The research shows that people select their strategies based on analytical methods which they choose because of their psychological approach to risk and their ability to control their behaviour. The data exhibits quasi-complete separation because the singular Hessian matrix warnings and elevated parameter estimates emerged as warning signs. The data shows that certain behavioural patterns can predict specific strategic preferences with high accuracy. The study improves directional inference through its results but decreases the reliability of coefficient estimates. The results show that stop-loss criteria lack significance because formal rule-setting does not determine strategy execution as underlying behavioural conviction and perceived effectiveness operate as more important factors. The analysis shows that investors match their analytical methods to their innate risk tolerance instead of using financial assessment benchmarks. Future studies need to improve generalizability through model stability assessment which requires both reduced category fragmentation and expanded sample size.

Conclusion

The research demonstrates that behavioural risk factors determine which stock evaluation methods retail investors select. The study found that demographic factors had moderate predictive ability while risk tolerance and trading behaviour showed much stronger predictive power. The investors who showed higher risk comprehension together with their active market engagement tended to use separate methods for evaluating performance. The investors who showed lower risk tolerance used conservative methods which resulted in specific patterns for their strategic decision-making. The empirical model demonstrates exceptional ability to explain the data but technical problems create coefficient estimation errors because of overfitting and limited data categories. The statistical limitations do not affect the directional result which shows that people choose their investment strategies based on their behaviour patterns instead of using base information. Risk psychology determines whether investors choose to use structured evaluation systems for their investment decisions.

The financial industry should understand that financial advisors and brokerage platforms need to connect their analytical methods with their understanding of client behaviour. Advisors should create investment strategies which match their clients' risk preferences because this approach increases investment success while decreasing investors' mental conflicts. The research should establish a broader participant base while improving measurement tools to create more reliable research results.

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