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"Analyzing The Investment Preferences And Decision-Making Strategies Of Retail Traders In The Indian Security Market"

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Abstract-. This research paper delves into the exploration of noise traders within the Indian security market, aiming to understand their characteristics, the tools they employ, and the influencing factors behind their trading decisions. Noise traders, driven by emotions, rumors, and other non-fundamental factors, play a significant role in shaping market dynamics. By analyzing their behavior, this study sheds light on the specific tools employed by these traders and examines the impact of time horizon and age on their trading decisions, with a focus on the importance they assign to various recommendations from different sources.To gather data for this research, consent was obtained from clients of various brokers, and data was collected through Google Survey Forms due to the wide geographic dispersion of respondents. By leveraging this data, the study uncovers valuable insights. The findings highlight that noise traders utilize diverse tools and analyses to inform their trading decisions. Additionally, they are influenced differently by recommendations provided through various channels.
This research contributes to the understanding of noise traders' behavior and their impact on asset prices within the Indian financial market. By exploring the psychology of traders and incorporating principles from behavioral finance, the study provides a comprehensive perspective on the dynamics of noise trading. The index terms encompass key concepts such as noise, Indian financial market, noise traders, psychology of traders, asset prices, and behavioral finance, encapsulating the central themes explored in this research paper.

Index Terms- Noise, Indian Financial Market, Noise Traders, Psychology of Traders, Asset Prices, Behavioral Finance.

I. INTRODUCTION

In the present scenario mostly in the process of coming out from the shock given by pandemic covid-19 the retail investor have been aggressively switching from common investment practices to investment in financial market. Traditional theories of financial markets have long assumed that prices are efficient and reflect all available information, implying predictability and rational decision-making by market participants. These theories emphasize the role of fundamental factors, such as earnings and dividends, in determining stock prices. However, the perception of asset prices varies between academics and financial market participants. The Efficient Market Hypothesis (EMH) defines an efficient market as one where rational investors compete to predict future security prices, with equal access to information. According to traditional theories, financial assets are always traded at their fundamental value, promptly incorporating any changes in future price expectations.However, in recent years, Behavioral Finance theories have gained prominence, challenging the assumptions of traditional finance. Behavioral Finance is a subfield of finance that explores how psychological and emotional factors influence investor behavior and market outcomes. Various theories within Behavioral Finance offer unique perspectives on the impact of human behavior on financial decision-making.

One influential theory, Prospect Theory, developed by Daniel Kahneman and Amos Tversky, suggests that people make decisions based on perceived gains and losses rather than objective outcomes. It posits that individuals are more sensitive to losses than gains, leading them to take excessive risks to avoid losses. Another theory, Overconfidence Bias, proposes that people tend to overestimate their abilities and underestimate the likelihood of negative events, resulting in the adoption of higher-risk strategies. Additionally, Herding Behavior theory suggests that individuals often imitate the actions of others rather than making independent decisions, leading to a collective influence on investment choices.The manifestation of these theories in action contributes to the introduction of "noise" in asset prices. Noise refers to random fluctuations and irrelevant information that impact asset prices, leading to short-term market volatility. It can arise from unexpected news events, rumors, sudden changes in investor sentiment, or irrational decision-making driven by emotions or cognitive biases. The presence of noise makes it challenging for investors to discern reliable signals about the true value of assets, potentially distorting prices and introducing market inefficiencies.Inefficient markets, such as the Indian security market, are more susceptible to noise due to factors like irrational investor behavior, information asymmetry, and market inefficiencies. This noise can result in price fluctuations unrelated to fundamental factors, such as a company's financial performance, but rather influenced by rumors, speculation, or emotional reactions.While noise is generally seen as a factor that reduces market efficiency and hinders informed decision-making, some economists argue that it can also serve a useful purpose by incorporating diverse perspectives and providing liquidity for buying and selling assets. Understanding the presence and impact of noise in the Indian security market is crucial for investors seeking to make well-informed decisions.

This research study focuses on the phenomenon of noise in Nifty futures prices—a popular financial instrument traded on the National Stock Exchange of India. Nifty futures allow traders to speculate on the future price of the Nifty index. However, due to the presence of noise, accurately predicting future prices becomes challenging. The study aims to identify and analyze the noise in Nifty futures prices, ultimately developing a model to enhance traders' ability to predict future prices more effectively.

In India, it is essential to encourage participation in the financial system from all sections of society to promote overall economic development. While the Indian middle class traditionally prioritizes saving income rather than investing, research has shown that developed economies with well-established financial markets often see over 50% participation from retail investors. In contrast, the participation of retail investors in risky assets remains relatively low in India. Common investment choices among retail investors involve putting money into banks or various government saving schemes, which provide returns sufficient to combat inflation. However, the financial market offers a range of assets with risk-adjusted returns, such as common equity, mutual funds, debt funds, government bonds, and derivatives.

In the wake of the COVID-19 pandemic, retail investors in India have increasingly shifted their investment practices towards the financial market as they recover from the shock of the crisis. Understanding the behavior and decision-making processes of retail investors, particularly regarding noise-based trading, is crucial in this evolving scenario.

II. MOTIVATION

The motivation to conduct present research originated by going through literature of Financial Markets based on characteristics of Noise Traders.Noise traders are individuals or investors who base their trading decisions on factors other than fundamental analysis, such as news headlines or rumors, and may act irrationally or emotionally. Understanding the characteristics of noise traders is important for financial professionals, as it can help them identify potential market inefficiencies and make more informed investment decisions. Here is a literature survey on the characteristics of noise traders:

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. This influential study explores the trading behavior and performance of individual investors, highlighting the detrimental impact of frequent trading on investment returns. (Year of publication: 2000).

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. This seminal work introduces prospect theory, which revolutionized the understanding of decision-making under risk by emphasizing the role of perceived gains and losses. (Year of publication: 1979).

DeBondt, W. F., & Thaler, R. (1985). Does the stock market overreact? This influential paper challenges the efficient market hypothesis by documenting the phenomenon of stock market overreaction, suggesting that investors tend to overreact to new information, leading to predictable patterns in stock prices. (Year of publication: 1985).

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. This study explores the disposition effect, a behavioral bias where investors tend to sell winning investments too early and hold onto losing investments for too long, impacting their overall investment performance. (Year of publication: 1985).

Thaler, R. H. (1999). Mental accounting matters. This paper discusses the concept of mental accounting, emphasizing how individuals categorize and treat money differently based on its source, leading to irrational financial decision-making. (Year of publication: 1999).

Barberis and Shleifer (2003) suggest that noise traders are overconfident, prone to overreacting to news and events, and may be influenced by their social networks or the behavior of other investors.

Hong and Stein (2003) argue that noise traders are more likely to hold onto their positions for longer periods, and may exhibit a preference for high-risk, high-return investments.

DeLong et al. (1990) propose that noise traders are often inexperienced or amateur investors who lack access to sophisticated financial tools and may trade on incomplete or biased information.

Baker and Wurgler (2006) find that noise traders may be more likely to engage in momentum trading, where they buy or sell assets based on recent price trends rather than fundamental analysis.

Cao and Wei (2005) suggest that noise traders may have different risk preferences than rational traders, and may be more influenced by emotions such as fear or greed.
Choe et al. (1999) propose that noise traders may be more likely to trade in volatile or illiquid markets, as they may be able to take advantage of price discrepancies or arbitrage opportunities.
Agata Kliber. et.al (2016) investigated the influence of age, gender, experience, and education while deciding to invest. The sampled population was connected to Warsaw Stock Exchange. Based on the ordered logistic regression model he concluded that Polish Female Investors were more risk-averse than males. Female investors are greatly influenced by expert opinion on investment decisions and man is a comparatively high-risk takers. A lesser educated investor takes more risks and trades more often than a highly educated investors. A trader having much lesser experience does take a large risk, uses technical analysis to take the trading decision, and estimates the risk of the portfolio based on standard deviation. Whereas more experienced traders take a lesser risk.
Reddings (1996) in his working paper on International Monitory Fund studied market microstructure and liquidity position of traders. He asserted that the market price of securities does deviate from their fundamental true value. The market price is affected by the presence of traders who do have incomplete information which can be termed as "Noise" and they participate in the market based on that information. He also asserts that cascading effect and Herd Behaviour are common phenomena that drive the trading decision of Investors.
De Long. et.al (2010) presented a simple overlapping generations model of an asset market in which irrational noise traders with erroneous different beliefs participate and affect asset prices and earn higher expected returns. The element of surprise by Noise trader reaction deters rational investors to trade against them. This also discourages sensible arbitrageurs from wagering against one other aggressively. As a result, prices may deviate greatly from fundamentals. Even in the absence of basic danger, values can be created. Furthermore, they can do this because of the disproportionate amount of danger that they produce. Noise traders are more likely than sensible investors to obtain a higher expected return.
Felix. et.al (2018) stressed that Financial Disclosure often has a "Noisy" signal embedded in them. This information is considered by many irrational traders as good to be true. The word choices and semantic context mislead the irrational noise trader and they take trading decisions based on this noise considered as information.
Timm O. Sprenger, and Isabell M. Welpe (2011) identified that news that is made available through reputed financial newspaper do affect stock prices. They segregated genuine news from ill-factored news from different media sources and studied their impact on the stock price of the companies included in the S&P 500. Our results show that the absolute value of cumulative returns before a news event is more pronounced for positive news than they are for negative news, suggesting more widespread information leakage before the good news.
Robert Bloomfield, Maureen O'Hara, and Gideon Saar (2007) explored the behavior of Noise Traders and how it affects the markets. They identified that the presence of Noise Traders enhances liquidity which can be judged by the lower spread and high volume and depth of the market. The noise traders temporarily reduce the chances of price reversal. They also identified that tax and transaction cost reduces the Noise Trader's activity.
Barber. et.al (2006) studied transaction data from 1983-2011 to conclude that Order Imbalance in transaction data indicates that rather often Buy (Sell) stocks in herds. They also take the same position in

the same stock that they have taken in the previous week (month). The Buy and Sell position in a particular stock during one year can forecast the return of the same stock next year. The stock that was bought heavily in one year tends to underperform stocks that were sold by an individual investor in the same year by 4.4% points.

Sanders. et.al (1997) applied the noise trader sentimental model to future markets. They identified that noise traders are either highly optimistic or pessimistic they in turn affect the market price of the security to make it greater or smaller than the fundamental value. This implies that future returns can't be predicted by assuming the level of Noise trader sentiments. They also conducted a test on the cross-section regression to identify that Noise traders do not create systematic biases in future prices.

Gervais and Odean (2001) find that noise traders are more likely to make speculative trades, where they take on high levels of risk in the hopes of achieving high returns.

Overall, the characteristics of noise traders vary depending on the specific context and market conditions. However, research suggests that noise traders may be more likely to make irrational or emotional decisions, may have different risk preferences than rational traders, and may be influenced by social networks or the behavior of other investors. Understanding these characteristics can help financial professionals identify potential market inefficiencies and make more informed investment decisions.

III. METHODOLOGY

The study aimed to investigate the characteristics of noise traders, specifically focusing on retail traders in India who are assumed to trade non-rationally based on noise information. To understand these characteristics, a survey-based descriptive cross-sectional research design was employed.To collect the necessary data, a survey was chosen as the method of data collection, and a self-drafted questionnaire was used as the data collection instrument. Given that the target respondents were retail participants of the stock market located in different states, it was decided to administer the survey through a Google Form. The survey was distributed to the sample elements either via email or by providing a Google link through WhatsApp numbers.

Population: The population for this study was defined as the cohort of all retail traders registered through various stock brokers across different states. According to the SEBI Investor Survey, the western zone accounted for 50% of all registered investors with a Demat Account. The southern zone had 7% investors, while the northern and eastern zones had 26% and 15% investors, respectively. These proportions were considered when determining the sample size and selecting sample elements for the study.

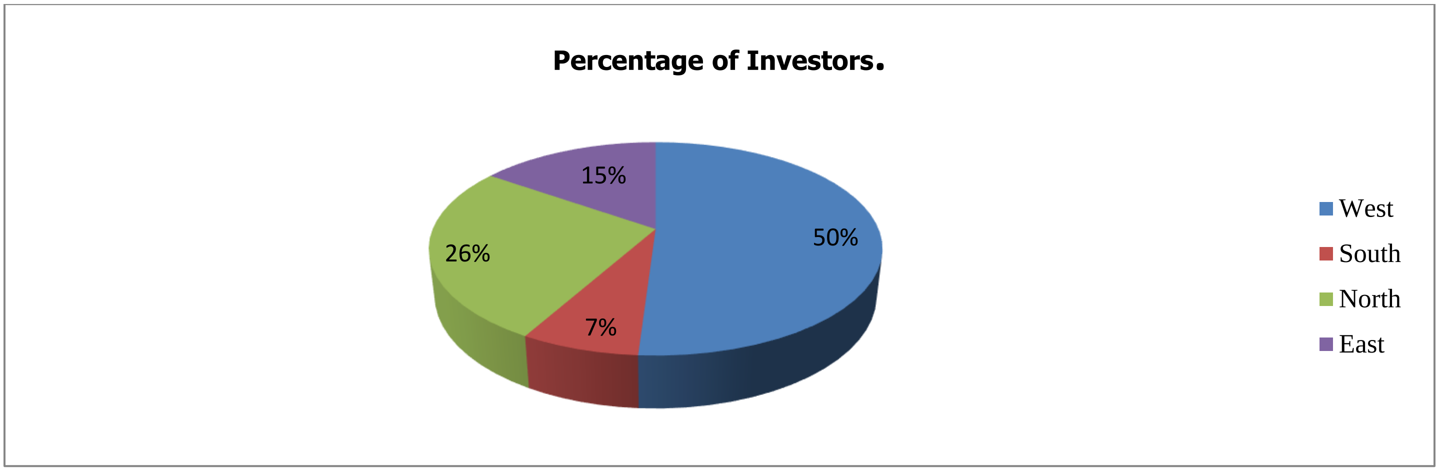

FIGURE 1 .PERCENTAGE OF INVESTORS IN VARIOUS ZONES.

Table 1.Sample Items from Various Zones

Broker	Zone	City	Client Communicated	Sample Used in Data Analysis
SMC	West	Mumbai	75	62
Angel Broking	West	Mumbai	104	95
Edeilwise	West	Mumbai	82	60
SMC	West	Ahmadabad	50	45
IIFL	North	Delhi	55	40
SMC	North	Jaipur	80	62
SMC	South	Banglore	105	82
SMC	South	Hyderabad	110	85
IIFL	East	Bhopal	105	87
Total			766	618

The table 1, provides a summary of sample items from different zones and brokers, along with the number of clients communicated and the sample used in data analysis.In the West zone, SMC broker in Mumbai communicated with 75 clients, out of which 62 were included in the data analysis. Angel Broking in Mumbai communicated with 104 clients, and 95 were included in the data analysis. Edelweiss in Mumbai communicated with 82 clients, and 60 were included in the data analysis. SMC in Ahmedabad communicated with 50 clients, and 45 were included in the data analysis.In the North zone, IIFL in Delhi communicated with 55 clients, and 40 were included in the data analysis. SMC in Jaipur communicated with 80 clients, and 62 were included in the data analysis.In the South zone, SMC in Bangalore communicated with 105 clients, and 82 were included in the data analysis. SMC in Hyderabad communicated with 110 clients, and 85 were included in the data analysis.In the East zone, IIFL in Bhopal communicated with 105 clients, and 87 were included in the data analysis.The total number of clients communicated across all zones and brokers was 766, and the total sample used in data analysis was 618. In order to investigate the characteristics of Noise Trader Following Hypothesis are formed—

Hypothesis of Association Based on Trader's Time Horizon of Investing and Demographic Factors:
H1: The age of the trader is not significantly associated with their time horizon of investing.
H2: The monthly income of the trader is not significantly associated with their time horizon of investing.
H3: The highest qualification of the trader is not significantly associated with their time horizon of investing.
H4: The profession of the trader is not significantly associated with their time horizon of investing.

Hypothesis of Difference Based on Age Group - Importance of Recommendations:
H5: There is no significant difference in the importance of broker recommendations for trading decisions among different age groups of traders.
H6: There is no significant difference in the importance of media recommendations for trading decisions among different age groups of traders.
H7: There is no significant difference in the importance of friend's recommendations for trading decisions among different age groups of traders.
H8: There is no significant difference in the importance of influencer recommendations for trading decisions among different age groups of traders.
H9: There is no significant difference in the importance of tweet recommendations for trading decisions among different age groups of traders.

Hypothesis of Difference Based on Trader's Time Horizon of Investing - Importance of Recommendations:
H10: There is no significant difference in the importance of broker recommendations for trading decisions among traders with different time horizons.
H11: There is no significant difference in the importance of media recommendations for trading decisions among traders with different time horizons.
H12: There is no significant difference in the importance of friend's recommendations for trading decisions among traders with different time horizons.
H13: There is no significant difference in the importance of influencer recommendations for trading decisions among traders with different time horizons.
H14: There is no significant difference in the importance of tweet recommendations for trading decisions among traders with different time horizons.

Hypothesis of Difference Based on Age Group and Time Horizon - Importance of Analysis:
H15: There is no significant difference in the importance of fundamental analysis for trading decisions among different age groups of traders.
H16: There is no significant difference in the importance of technical analysis for trading decisions among different age groups of traders.

H17: There is no significant difference in the importance of fundamental analysis for trading decisions among traders with different time horizons.
H18: There is no significant difference in the importance of technical analysis for trading decisions among traders with different time horizons.

IV. RESULT AND DISCUSSION

Table 2 Cross Tabulation Analysis between Age of Retail Traders and their Time Horizon of Investing.

Age of Trader * Time Horizon of Investing Cross tabulation								
Age Category			Time Horizon of Investing					Total
			Very Long Term > 1 Year	Long Term 6 Month -1 Year	Very Short Term <1 Month	Intraday < 1 Day	Scalping - a few Minutes	
	15-20	Count	0	0	9	18	18	45
		% within the Age of Trader	0.0%	0.0%	20.0%	40.0%	40.0%	100.0%
	20-30	Count	0	9	27	180	9	225
		% within the Age of Trader	0.0%	4.0%	12.0%	80.0%	4.0%	100.0%
	30-40	Count	0	0	18	72	18	108
		% within the Age of Trader	0.0%	0.0%	16.7%	66.7%	16.7%	100.0%
	>40	Count	72	27	0	9	0	108
		% within the Age of Trader	66.7%	25.0%	0.0%	8.3%	0.0%	100.0%
Total		Count	72	36	54	279	45	486
		% within the Age of Trader	14.8%	7.4%	11.1%	57.4%	9.3%	100.0%

Table 3 Test of Association between Age of Retail Traders and their Time Horizon of Investing

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	468.693[a]	12	.000
a. 2 cells (10.0%) have an expected count of less than 5. The minimum expected count is 3.33.			

In the 15-20 age category, all traders engage in short-term investment strategies, with 40% focusing on intraday trading and the remaining 60% split equally between very short-term trading and scalping. No traders in this age group have a long-term investment outlook.

For traders aged 20-30, the majority (80%) prefer intraday trading, indicating a significant inclination towards short-term investment strategies. A smaller percentage (4%) engage in both long-term trading and scalping, while 12% opt for a very short-term time horizon.

In the 30-40 age group, intraday trading remains the most popular choice (67%), followed by a mix of very short-term trading (17%) and scalping (17%). None of the traders in this age category have a long-term investment horizon.

Traders above 40 years old exhibit a different pattern, with 67% favoring very long-term investments, indicating a more patient and strategic approach. A quarter of traders in this age group have a long-term outlook, while a smaller portion (8%) engage in intraday trading. None of the traders in this category practice scalping.

Table 3 presents the results of the chi-square test that examines the association between the age of retail traders and their preferred time horizon of investing. The test measures the likelihood that the observed association between the variables is due to chance.

The Pearson Chi-Square value is 468.693, with 12 degrees of freedom. The associated p-value is reported as .000 (which is less than the conventional significance level of .05). This indicates that the relationship between age and time horizon of investing is statistically significant. Subsequently H_1 is rejected.

Table 4 Cross Tabulation Analysis between Monthly Income of Retail Traders and their Time Horizon of Investing.

Monthly Income * Time Horizon of Investing Cross tabulation								
			Time Horizon of Investing					Total
Monthly Income			Very Long Term > 1 Year	Long Term 6 Month -1 Year	Very Short Term <1 Month	Intraday < 1 Day	Scalping - a few Minutes	
	10,000-30,000	Count	0	9	36	72	18	135
		% within Monthly Income	0.0%	6.7%	26.7%	53.3%	13.3%	100.0%
	30,000-60,000	Count	36	0	9	108	9	162
		% within Monthly Income	22.2%	0.0%	5.6%	66.7%	5.6%	100.0%
	60,000>1 Lakh	Count	36	9	0	54	0	99
		% within Monthly Income	36.4%	9.1%	0.0%	54.5%	0.0%	100.0%
	>1 Lakh	Count	0	18	9	45	18	90
		% within Monthly Income	0.0%	20.0%	10.0%	50.0%	20.0%	100.0%

Total	Count	72	36	54	279	45	486
	% within Monthly Income	14.8%	7.4%	11.1%	57.4%	9.3%	100.0%

Table 5 Test of Association between Monthly Income of Retail Traders and their Time Horizon of Investing.

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	176.120[a]	12	.000

Table 4 presents a cross-tabulation analysis of the relationship between the monthly income of retail traders and their preferred time horizons for investing. The table provides insights into the distribution of traders across different income brackets and the corresponding time horizons they adopt.

For traders earning between 10,000 and 30,000, the majority (53.3%) prefer an intraday time horizon, indicating a focus on short-term trading. Additionally, 26.7% engage in very short-term trading, while 13.3% opt for scalping. No traders in this income bracket have a long-term investment outlook.

In the income bracket of 30,000 to 60,000, a significant portion (66.7%) of traders prefer an intraday time horizon, demonstrating a preference for short-term trading. Additionally, 5.6% engage in very short-term trading, while 5.6% opt for scalping. Surprisingly, none of the traders in this income bracket have a long-term investment outlook.

Traders earning between 60,000 and 1 Lakh also exhibit a strong inclination towards intraday trading, with 54.5% adopting this time horizon. Meanwhile, 36.4% have a very long-term investment outlook, while 9.1% engage in long-term trading.

For traders earning more than 1 Lakh, the preference for intraday trading remains strong at 50%. A significant portion (20%) engage in both long-term trading and scalping, indicating a diverse range of time horizons within this income bracket. None of the traders in this category have a very long-term outlook.. Subsequently H_2 is rejected.

Table 6 : Cross Tabulation between the Highest Educational Qualification of Retail Traders and their Time Horizon of Investing.

Highest Educational Qualification * Time Horizon of Investing Cross tabulation								
			Time Horizon of Investing					Total
Highest Qualification			Very Long Term > 1 Year	Long Term 6 Month -1 Year	Very Short Term <1 Month	Intraday < 1 Day	Scalping - a few Minutes	
		Count	0	0	0	9	0	9

	Higher Secondary	% within Highest Educational Qualification	0.0%	0.0%	0.0%	100.0%	0.0%	100.0 %
	Graduate	Count	45	9	18	126	36	234
		% within Highest Educational Qualification	19.2%	3.8%	7.7%	53.8%	15.4%	100.0 %
	Post Graduate	Count	27	18	36	126	9	216
		% within Highest Educational Qualification	12.5%	8.3%	16.7%	58.3%	4.2%	100.0 %
	Doctorate	Count	0	9	0	18	0	27
		% within Highest Educational Qualification	0.0%	33.3%	0.0%	66.7%	0.0%	100.0 %
Total		Count	72	36	54	279	45	486
		% within Highest Educational Qualification	14.8%	7.4%	11.1%	57.4%	9.3%	100.0 %

Table 7 Test of Association between Highest Qualification of Retail Traders and their Time Horizon of Investing.

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	73.741[a]	12	.000

Table 6 presents a cross-tabulation analysis between the highest educational qualification of retail traders and their preferred time horizons for investing. The table provides counts and percentages of traders in different educational qualification categories and their corresponding time horizons.

In the "Higher Secondary" qualification category, all traders (100%) have an intraday time horizon, indicating a preference for short-term trading. No traders in this category engage in very long-term, long-term, or scalping strategies.

Among traders with a "Graduate" qualification, the majority (53.8%) prefer an intraday time horizon, while a significant portion (19.2%) have a very long-term investment outlook. Additionally, 7.7% engage in long-term trading, and 15.4% opt for scalping.

Traders with a "Post Graduate" qualification also exhibit a strong inclination towards intraday trading (58.3%). Furthermore, 16.7% engage in very short-term trading, and 8.3% have a long-term time horizon. Scalping is preferred by 4.2% of traders in this category.

In the "Doctorate" qualification category, all traders (100%) have an intraday time horizon, indicating a preference for short-term trading. Some traders (33.3%) also engage in long-term trading. No traders in this category have a very long-term or scalping time horizon. Table 7 presents the results of the chi-square test that examines the association between the highest qualification of retail traders and their preferred time horizons of investing. The test measures the likelihood that the observed association between the variables is due to chance.

The Pearson Chi-Square value is 73.741, with 12 degrees of freedom. The associated p-value is reported as .000 (which is less than the conventional significance level of .05). This indicates that the relationship between the highest qualification and time horizon of investing is statistically significant. The significant chi-square value suggests that there is an association between the highest qualification of retail traders and their preferred time horizons for investing. In other words, the highest qualification appears to influence the time horizon choices of traders. However, it is important to note that the chi-square test does not provide information about the strength or direction of the association, only its significance.

Table 8 Cross Tabulation between the Profession of Retail Traders and their Time Horizon of Investing.

The profession of Trader * Time Horizon of Investing Cross tabulation									
Profession			Time Horizon of Investing					Total
			Very Long Term > 1 Year	Long Term 6 Month - 1 Year	Very Short Term <1 Month	Intraday < 1 Day	Scalping - a few Minutes	
	Private	Count	27	27	45	171	9	279
		% within the Profession of Trader	9.7%	9.7%	16.1%	61.3%	3.2%	100.0%
	Government	Count	27	0	0	9	0	36
		% within the Profession of Trader	75.0%	0.0%	0.0%	25.0%	0.0%	100.0%
	Public	Count	0	0	0	18	27	45
		% within the Profession of Trader	0.0%	0.0%	0.0%	40.0%	60.0%	100.0%
	Business	Count	18	9	0	36	0	63
		% within the Profession of Trader	28.6%	14.3%	0.0%	57.1%	0.0%	100.0%
	Other	Count	0	0	9	45	9	63
		% within the Profession of Trader	0.0%	0.0%	14.3%	71.4%	14.3%	100.0%

Total	Count	72	36	54	279	45	486
	% within the Profession of Trader	14.8%	7.4%	11.1%	57.4%	9.3%	100.0%

Table 9 Test of Association between Profession of Retail Traders and their Time Horizon of Investing.

Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	315.398[a]	16	.000

Table 8 presents a cross-tabulation analysis between the profession of retail traders and their preferred time horizons for investing. The table provides counts and percentages of traders in different professions and their corresponding time horizons.

Among private sector traders, the majority (61.3%) prefer an intraday time horizon, indicating a focus on short-term trading. Additionally, 16.1% engage in very short-term trading, while 9.7% have both very long-term and long-term investment outlooks. A small percentage (3.2%) of private sector traders opt for scalping.

In the government sector, the majority (75%) of traders have a very long-term time horizon, indicating a preference for long-term investment strategies. The remaining 25% have an intraday time horizon.

Traders in the public sector exhibit a strong inclination towards intraday trading, with 40% adopting this time horizon. Furthermore, 60% engage in scalping, indicating a preference for very short-term trading.

Among traders in business, the majority (57.1%) prefer an intraday time horizon, while 28.6% have a very long-term investment outlook. Additionally, 14.3% engage in long-term trading.

In the "Other" category, the majority (71.4%) of traders have an intraday time horizon, indicating a preference for short-term trading. Some traders (14.3%) also engage in very short-term trading, while 14.3% opt for scalping.

Table 9 presents the results of the chi-square test that examines the association between the profession of retail traders and their preferred time horizons for investing. The test evaluates whether the observed association between the variables is statistically significant or likely due to chance.

The Pearson Chi-Square value is 315.398, with 16 degrees of freedom. The associated p-value is reported as .000 (which is less than the conventional significance level of .05). This indicates that the relationship between the profession of traders and their time horizons of investing is statistically significant.

The significant chi-square value suggests that there is a strong association between the profession of retail traders and their preferred time horizons for investment. In other words, the profession of traders appears to influence the choices of time horizons in their investment strategies. However, the chi-square test does not provide information about the strength or direction of the association, only its significance. Subsequently, H_4 was rejected

Table 10 Test of Significance, using ANOVA, to the importance attached to various Recommendations by retail traders groups based on Age.

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Broker Recommendation Importance	Between Groups	39.873	3	13.291	38.256	.000
	Within Groups	167.460	482	.347		
	Total	207.333	485			
Media Recommendation Importance	Between Groups	5.543	3	1.848	12.152	.000
	Within Groups	73.290	482	.152		
	Total	78.833	485			
Friend's Recommendation Importance	Between Groups	5.793	3	1.931	10.633	.000
	Within Groups	87.540	482	.182		
	Total	93.333	485			
Importance of Influencer	Between Groups	60.859	3	20.286	25.801	.000
	Within Groups	378.979	482	.786		
	Total	439.837	485			
Importance of Tweet Recommendation	Between Groups	4.417	3	1.472	2.241	.083
	Within Groups	316.704	482	.657		
	Total	321.121	485			

Table 10 presents the results of the ANOVA tests conducted to assess the significance of the recommendations' importance among different age groups of retail traders. The table provides information about the sum of squares, degrees of freedom, mean squares, F-values, and p-values for each recommendation category.

H4: Broker Recommendation Importance

The F-value for Broker Recommendation Importance is 38.256, and the associated p-value is .000, which is less than the significance level of .05. This indicates that there is a significant difference in the importance attached to broker recommendations among different age groups of retail traders.

H5: Media Recommendation Importance

The F-value for Media Recommendation Importance is 12.152, and the p-value is .000, indicating a significant difference in the importance attached to media recommendations among different age groups of retail traders.

H6: Friend's Recommendation Importance

The F-value for Friend's Recommendation Importance is 10.633, and the p-value is .000, indicating a significant difference in the importance attached to recommendations from friends among different age groups of retail traders.

H7: Importance of Influencer

The F-value for Importance of Influencer is 25.801, and the p-value is .000, indicating a significant difference in the importance attached to influencer recommendations among different age groups of retail traders.

H8: Importance of Tweet Recommendation

The F-value for Importance of Tweet Recommendation is 2.241, and the p-value is .083, which is greater than the significance level of .05. This suggests that there is no significant difference in the importance attached to tweet recommendations among different age groups of retail traders. Subsequently H_5, H_6, H_7, and H_8 are rejected and H_9 is accepted.

Table 11 Mean value of importance attached to various Recommendations by retail traders groups based on the Time Horizon of Investing.

Statistics					
	Time Horizon of Investing				
	Very Long Term > 1 Year	Long Term 6 Month -1 Year	Very Short Term <1 Month	Intraday < 1 Day	Scalping - a few Minutes
	Mean	Mean	Mean	Mean	Mean
Broker Recommendation Importance	2.75	2.25	2.00	2.45	2.20
Media Recommendation Importance	2.88	3.00	3.00	2.74	2.60
Friend's Recommendation Importance	1.25	1.50	1.17	1.29	1.00
Importance of Influencer	2.75	2.25	3.33	3.01	2.20
Importance of Tweet Recommendation	1.3750	2.0000	1.5370	1.5591	1.6444

Table 12 Test of Significance, using ANOVA, to the importance attached to various Recommendations by retail traders groups based on the Time Horizon of Investing.

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Importance of Broker Recommendation	Between Groups	20.787	4	5.197	13.399	.000

	Within Groups	186.547	481	.388		
	Total	207.333	485			
Importance of Media Recommendation	Between Groups	6.739	4	1.685	11.240	.000
	Within Groups	72.094	481	.150		
	Total	78.833	485			
Importance of Friend's Recommendation	Between Groups	5.849	4	1.462	8.040	.000
	Within Groups	87.484	481	.182		
	Total	93.333	485			
Importance of Influencer	Between Groups	52.445	4	13.111	16.279	.000
	Within Groups	387.393	481	.805		
	Total	439.837	485			
Importance of Tweet Recommendation	Between Groups	9.735	4	2.434	3.759	.005
	Within Groups	311.386	481	.647		
	Total	321.121	485			

Table 11 provides the mean values of the importance attached to various recommendations by retail traders based on their time horizon of investing. Each row represents a different recommendation category, and each column represents a specific time horizon.

H10: Importance of Broker Recommendation

The mean values for the importance of broker recommendation vary across different time horizons of investing, ranging from 2.00 to 2.75. These values suggest that retail traders who have a very long-term time horizon assign a higher importance to broker recommendations compared to those with shorter time horizons.

H11: Importance of Media Recommendation

The mean values for the importance of media recommendation range from 2.74 to 3.00 across different time horizons. Retail traders with a long-term time horizon tend to attach higher importance to media recommendations.

H12: Importance of Friend's Recommendation

The mean values for the importance of friend's recommendation range from 1.00 to 1.50 across different time horizons. Retail traders with a very short-term time horizon attach relatively lower importance to friend's recommendations.

H13: Importance of Influencer

The mean values for the importance of influencer recommendation vary across different time horizons, ranging from 2.25 to 3.33. Retail traders with a very short-term and short-term time horizon attach higher importance to influencer recommendations compared to those with longer time horizons.

H14: Importance of Tweet Recommendation

The mean values for the importance of tweet recommendation range from 1.3750 to 2.0000 across different time horizons. Retail traders with a very long-term time horizon tend to assign a lower importance to tweet recommendations.
Table 12 presents the results of the ANOVA tests conducted to assess the significance of the differences in the importance attached to various recommendations based on the time horizon of investing.
The ANOVA results indicate that there are significant differences in the importance attached to broker recommendations, media recommendations, friend's recommendations, influencer recommendations, and tweet recommendations across different time horizons of investing. The p-values for all these recommendations are less than the significance level of .05, suggesting that the time horizon of investing does play a significant role in determining the importance attached to different recommendation sources. Subsequently, H_{10}, H_{11}, H_{12}, H_{13}, are $H_{14}$are rejected.

Table 13 Mean value of importance attached to Technical and Fundamental Analysis by retail traders groups based on the Time Horizon of Investment.

Statistics					
	Time Horizon of Investing				
	Very Long Term > 1 Year	Long Term 6 Month -1 Year	Very Short Term <1 Month	Intraday < 1 Day	Scalping - a few Minutes
	Mean	Mean	Mean	Mean	Mean
Importance of Fundamental Analysis	3.88	3.75	1.83	2.03	1.80
Importance of Technical Analysis	1.75	2.50	4.67	4.06	4.00

Table 14 Test of Significance, using ANOVA, to the importance attached to Technical and Fundamental Analysis by retail traders groups based on the Time Horizon of Investment.

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Importance of Fundamental Analysis	Between Groups	293.46	4	73.36	92.85	.000
	Within Groups	380.03	481	0.790		
	Total	673.50	485			
Importance of Technical Analysis	Between Groups	416.66	4	104.16	116.69	.000
	Within Groups	429.33	481	0.893		
	Total	846.00	485			

Table 13 presents the mean values of the importance attached to technical and fundamental analysis by retail traders based on their time horizon of investment. Each row represents a different analysis type, and each column represents a specific time horizon.

H15: Importance of Fundamental Analysis

The mean values for the importance of fundamental analysis vary across different time horizons of investment, ranging from 1.80 to 3.88. Retail traders with a very long-term time horizon assign the highest importance to fundamental analysis, whereas those with a very short-term and intraday time horizon attach relatively lower importance to it.

H16: Importance of Technical Analysis

The mean values for the importance of technical analysis range from 1.75 to 4.67 across different time horizons. Retail traders with a very short-term, intraday, and scalping time horizon attach higher importance to technical analysis compared to those with longer time horizons.

Table 14 presents the results of the ANOVA tests conducted to assess the significance of the differences in the importance attached to technical and fundamental analysis based on the time horizon of investment.

The ANOVA results indicate that there are significant differences in the importance attached to fundamental analysis and technical analysis across different time horizons of investment. The p-values for both analyses are less than the significance level of .05, suggesting that the time horizon of investment plays a significant role in determining the importance attached to technical and fundamental analysis. Subsequently, H_{15}, H_{16}, H_{17}, and H_{18} are rejected at 95%confidence interval.

V. CONCLUSION

In conclusion, the research conducted in this chat session provides valuable insights into the preferences, behaviors, and decision-making strategies of retail traders in the financial markets. The analysis of various tables and statistical tests has shed light on key findings regarding the relationship between different demographic factors and the time horizons of investing among retail traders.

Firstly, the age of traders has been identified as a significant determinant of their preferred time horizons. Younger traders tend to engage in short-term trading, while older traders adopt longer time horizons. This suggests that age plays a role in shaping traders' investment strategies and time frames.

Secondly, the monthly income of traders has shown a correlation with their time horizons of investing. Higher-income traders exhibit a wider range of time horizons, including both short-term and long-term approaches. However, regardless of income, the majority of traders still show a preference for short-term and intraday trading.

Thirdly, the educational qualification of traders has also been found to influence their time horizons. While traders across all qualification categories prefer short-term and intraday trading, those with higher qualifications, such as Post Graduates and Doctorates, display a greater diversity of time horizons, including long-term strategies.

Furthermore, the profession of retail traders has been shown to have an impact on their preferred time horizons. Traders from different professions exhibit varied preferences, ranging from long-term to short-term strategies. This finding highlights the role of profession in shaping traders' investment behaviors and strategies.

Lastly, the importance attached to different recommendation sources and analyses varies based on the age of traders. Broker recommendations, media recommendations, friend's recommendations, and influencer recommendations differ significantly among different age groups, while tweet recommendations do not show a significant difference in importance.

These key findings collectively contribute to a deeper understanding of the preferences and decision-making processes of retail traders. The research emphasizes the significance of demographic factors in shaping traders' investment strategies and time horizons. These insights can be valuable for market analysts, financial institutions, and policymakers in catering to the diverse needs of retail traders and designing appropriate strategies and recommendations tailored to their specific demographic profiles. It is essential to consider the time horizon as a crucial factor when studying and analyzing the behaviours of retail traders in the financial markets.

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