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A STUDY ON INVESTOR AWARENESS AND PERCEPTION TOWARDS ALGORITHMIC TRADING IN GUJARAT

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ABSTRACT

Algorithmic trading accounts for a large share of the order flow on Indian stock exchanges, but many retail investors know little about how it works. This study examines the awareness and perception of investors towards algorithmic trading in Gujarat. The objectives were to measure the level of investor awareness towards algorithmic trading and to examine the relationship between investor awareness and perception. Primary data were collected through a structured questionnaire based on a five-point Likert scale. A sample of 150 investors was drawn from Ahmedabad, Surat, Vadodara and Rajkot by simple random sampling. The data were analysed using descriptive statistics, one-sample t test, independent samples t test, one-way ANOVA, chi-square test, Pearson correlation and simple linear regression. The results show that awareness of investors is at a moderate level (mean = 3.09), while their perception is favourable (mean = 3.48). Awareness differs significantly with investing experience, but not with gender, age or education. Awareness has a strong positive relationship with perception ($r = 0.58$, $p < 0.001$) and explains about 34 per cent of the variation in it. The study concludes that investor education by brokers, exchanges and regulators can raise awareness and support better informed views.

KEYWORDS: Algorithmic Trading, Investor Awareness, Investor Perception, Retail Investors, Gujarat, Stock Market

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1. INTRODUCTION

The stock market plays an important role in the economy of a country. It helps companies to raise money for their growth and gives people a chance to invest their savings and earn returns. In India, the number of people who invest in shares has grown very fast in the last few years. Earlier, investing in the stock market was seen as something only rich people or business families did. Today, a salaried person, a small shopkeeper or even a college student can open a demat account in a few minutes using a mobile phone. Low brokerage, easy mobile apps and a large amount of information on social media have brought many new investors into the market.

Along with this growth, the way trading is done has also changed. In the early days, buyers and sellers used to shout and signal to each other on the trading floor of the exchange. After the National Stock Exchange started screen based trading in 1994, orders began to move through computers, and trading became faster and more open. The next big step was the use of computer programs that can take trading decisions and place orders on their own. This is called algorithmic trading, or simply algo trading.

In simple words, algorithmic trading means buying and selling of shares by a computer program that follows a fixed set of rules. These rules are set in advance and may be based on price, quantity, time or other measures (Bunkar & Ramaiah, 2024). For example, a program can

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be told to buy a share when its price goes above a certain level and to sell it when the price falls by two per cent. Once the rules are set, the program keeps watching the market and sends the order in a fraction of a second, without waiting for a person to click a button. Because of this, an algorithm can handle many orders at the same time, which is very difficult for a human trader.

Algorithmic trading has many benefits. It is fast, it can reduce the cost of trading, and it removes fear and greed from the decision because the program follows the plan it has been given. At the same time, there are some risks. A small mistake in the rules or in the computer code can cause wrong orders and quick losses. Failure of the system or the internet connection can also create problems. Researchers have pointed out that the speed and complexity of such systems can lead to operational risks, and that high speed trading has been linked with sudden price falls in some markets (Rahat et al., 2023). Many small investors also feel that big institutions with better technology get an unfair advantage over them.

India has seen a rapid rise in algorithmic trading. The Securities and Exchange Board of India (SEBI) issued guidelines on algorithmic trading on 30 March 2012, and one study notes that India reached a high share of algorithmic trades in a much shorter time than the United States did (Bunkar & Ramaiah, 2024). Most of this activity has come from large institutions and professional trading firms. In recent years, however, some brokers and technology firms have started offering platforms that allow even small investors to use ready made strategies or to build simple rule based strategies without writing any code. This means that algorithmic trading is no longer limited to big players. A common investor may now be asked to use it, or may be affected by it, even without knowing much about it.

In this situation, two things become important, namely awareness and perception. Awareness means whether an investor knows that algorithmic trading exists, understands how it works, and knows about the rules and risks connected with it. Perception means the opinion, belief and feeling that an investor has about it, for example whether it is seen as useful, safe, costly or fair. Both are closely linked with each other. An investor who knows more about a technology is likely to form a clearer opinion about it, and that opinion then decides whether the investor will use it, avoid it or trust it. A study on Indian retail investors found that awareness has a positive effect on the intention to use algorithmic trading platforms, and that trust and acceptance of new ideas also play a part (Bunkar & Ramaiah, 2024).

Gujarat is a suitable place to study this topic. The state has a long history of trade and business, and people here have a strong habit of investing in shares and other market products. Cities such as Ahmedabad, Surat, Vadodara and Rajkot have many active investors and a good number of local brokers and sub brokers. The state also has GIFT City, which has been developed as an international financial services centre. With so much market activity and the growing use of digital platforms, it is useful to know how much the investors of Gujarat understand about algorithmic trading and what they think about it.

The present study tries to measure the awareness of investors of Gujarat towards algorithmic trading and to see how this awareness is related to their perception. Primary data were collected from 150 investors of four major cities of the state with the help of a structured questionnaire, and the data were studied with the help of simple statistical tools. The paper is arranged in the following order. After this introduction, the need of the study and a review of earlier work are given. The objectives, sample size and sampling technique follow. Then the data are analysed, and finally the conclusion and suggestions are presented.

2. NEED OF THE STUDY

Algorithmic trading is growing in India, but most of the talk about it is about big institutions and professional traders. Ordinary investors are the largest group in the market in terms of number, and they are also the group that is least informed about how algorithmic trading works. When a new technology enters the market faster than the knowledge of the people who use the market, there is a risk that investors will either stay away from useful tools or use them without proper understanding. Both situations are harmful. This makes it necessary to find out how much investors really know.

A second reason for this study is the lack of local evidence. Most of the Indian studies in this area have been done on robo advisors or on investors from the whole country, and many of them have used purposive or snowball sampling, where the respondents are chosen by the researcher or through personal contacts (Verma et al., 2025; Verma et al., 2026). Such samples may not represent all investors. Very few studies have focused on a single state, and no study known to the researcher has measured the awareness and perception of algorithmic trading among the investors of Gujarat using a random sample. Gujarat has a very active investor base, so the findings of other regions cannot simply be applied here.

The third reason is investor protection. As algorithmic trading tools become easier to reach, there is a chance that some investors will buy ready made strategies from unknown sellers who promise high or sure returns. An investor who does not know about the rules, the approval needed for strategies and the risk of system failure can easily be misled. Studies show that trust is one of the main factors that decide whether investors accept or reject algorithmic trading (Rahat et al., 2023; Bunkar & Ramaiah, 2024). Trust that is built on proper knowledge is safer than trust that is built on advertisements. A study of awareness will show where the gaps are.

Brokers, stock exchanges and financial technology companies also need this kind of information. If investors have a low level of awareness or a doubtful view about algorithmic trading, the companies that offer such services cannot expect a good response, however good the product may be. By knowing which groups of investors are less aware, for example new investors or those with less experience, firms can plan training sessions, simple videos and demonstration accounts for the right people instead of spending money on all investors in the same way.

Regulators and policy makers can also gain from the results. SEBI and the exchanges run many investor education programmes. If the findings show that awareness is low about specific points such as rules, approvals and risks, the programmes can be made more useful by giving more attention to those points. Earlier work has also suggested that regulators should promote awareness and build a safe environment for algorithmic trading (Bunkar & Ramaiah, 2024).

From the academic side, the study adds to the limited research on algorithmic trading from the point of view of the investor. It does not only describe the level of awareness and perception but also tests whether the two are related, and whether awareness differs among investors with different personal features such as gender, age, education and experience. The use of a random sample from four cities also makes the results more dependable than those based on convenience samples. For these reasons, the study is both timely and useful.

3. LITERATURE REVIEW

Irimia-Diéguez, Velicia-Martín and Aguayo-Camacho (2023) studied how attitude, social norms and perceived control affect the intention to use, and the actual use of, fintech services. Data were collected from 300 companies and analysed with partial least squares structural equation modelling. The results supported the theory of reasoned action and the theory of planned behaviour. Both attitude and social norms were found to be important in forming the intention to use, and a good part of the effect of social norms on intention passed through attitude. The respondents in this study were companies and not individual investors, but the finding is useful for the present work because it shows that what a person feels about a financial technology, and what the people around that person think of it, decide whether it is accepted.

Nain and Rajan (2023) explored the present state of robo advisory services in India through a qualitative study. Interview data were written out and studied with the help of content analysis. The study found that robo advisory rests on three pillars, namely ease and convenience, saving of time, and transparency in operations. The authors also concluded that these services are still at an early stage in India and that they are still new in developing countries when compared with developed countries. The study is among the first to bring out the problems faced by financial technology firms that serve the Indian market.

Rahat, Siddiqui, Pervez and Hasan (2023) looked at the reasons why traders and investors of a conventional

stock exchange hesitate to adopt algorithmic trading, taking the Pakistan Stock Exchange as the case. A questionnaire was filled by 50 traders and investors chosen by convenience sampling, and the data were analysed with correlation and linear regression. Trust was found to be the biggest hurdle, because investors have doubts about a system that has little human contact and depends on machines. Fear of wrong calculations and the lack of experienced data engineers were also reasons for the reluctance. Lack of interest from the government, unnecessary investment and fear of unemployment also had a significant effect on adoption. Lack of awareness was the least important factor, which showed that the respondents were already fairly aware of algorithmic trading, although the authors warned that the small sample does not allow the results to be generalised.

Bunkar and Ramaiah (2024) investigated the effect of awareness of algorithmic trading, trust in algorithmic trading and acceptance of innovativeness on the intention to use algorithmic trading platforms among Indian investors. A structured questionnaire with a five-point Likert scale was used to collect data from 392 retail investors through purposive sampling, and structural equation modelling was used to test the serial mediation. The findings show that investor awareness has a significant and positive effect on the intention to use algorithmic trading platforms. Trust in the platforms and acceptance of innovation also influenced the decision to use, both on their own and as mediators between awareness and intention. The authors suggested that investment regulators should promote technological awareness, build trust and provide a safe environment for retail investors.

Parveen, Kesharwani, Prakash and Gangwar (2024) reviewed the literature on robo advisors from 2008 to 2024, using papers mainly from Google Scholar and some from Scopus. They found that adoption is driven by factors such as age group, financial literacy and trust in technology, and that in India robo advisors attract mostly younger and male investors, with more use of the platforms during times of market volatility. The review also noted that artificial intelligence helps to personalise the services, but that the regulatory frameworks are still not enough, especially for risk management. The authors recommended that future research should give attention to regulation, explainable artificial intelligence and anti-money laundering measures.

Akhtar, Akhtar and Laeeq (2025) reviewed how robo advisors have developed over time and set out a plan for future research. Later studies that refer to this review point out that the level of human involvement in the advice, that is, whether the advice is fully automatic or mixed with a human adviser, can change the way investors look at these services. This shows that the perception of automated investing is not the same for all types of services.

Verma, Schulze, Goswami and Upreti (2025) studied the resistance of Indian retail investors towards financial robo advisors using innovation resistance theory. Data were collected from 409 investors through purposive sampling and analysed with structural equation modelling. All the barriers under study, except the value barrier, were found to increase resistance, and inertia, that is, the habit of staying with the old way, was the strongest of them. A positive attitude towards artificial intelligence weakened the effect of inertia, overconfidence bias and data privacy risk on resistance. The study also found that this resistance reduces the intention to use and to recommend robo advisors.

de Oliveira Santini, Hasan Jafar, Junior Ladeira and Rasul (2026) carried out a meta analysis of the drivers of robo advisor adoption in financial services. A meta analysis combines the results of many earlier studies, which is useful because single studies often give different results for the same factor. Later work refers to this study to explain that in emerging markets such as India, the uptake of robo advisors depends on user related factors, including readiness for digital services and the perceptions of the users (Verma et al., 2026).

Goswami and Verma (2026) examined why investors resist financial robo advisors, looking at the matter from a psychological point of view. The study moves the attention from the reasons for accepting such services to the reasons for refusing them, and treats the refusal as something connected with the thinking and feeling of the investor and not only with the technical quality of the service. This supports the idea that the perception of an investor is an important

part of any study on automated investing.

Verma, Remer, Goswami and Sinha (2026) collected data from 397 Indian investors through purposive sampling and compared three well known adoption models for financial robo advisors, namely the theory of planned behaviour, the second unified theory of acceptance and use of technology, and the self-efficacy based value adoption model. The self-efficacy based model explained the most variation in the intention to use (73.4 per cent), followed by the unified theory (70.8 per cent) and the theory of planned behaviour (58.2 per cent). An integrated model explained 82.8 per cent of the variation in intention. Attitude, perceived value, self-efficacy, performance expectancy, effort expectancy, enjoyment with habit, and social and control perception were all significant. The effect of self-efficacy was strong for fully automated robo advisors but not for hybrid ones, whereas attitude, effort expectancy and performance expectancy mattered more for hybrid services.

The studies reviewed above show some clear points. First, awareness, trust and attitude are repeatedly found to affect the acceptance of automated investing. Second, most of the research from India is about robo advisors, and among the studies reviewed only one (Bunkar & Ramaiah, 2024) deals directly with algorithmic trading platforms among Indian retail investors. Third, the samples in these studies were mostly selected by purposive, snowball or convenience methods, and none of them focused on Gujarat. The present study tries to fill these gaps by measuring both the awareness and the perception of algorithmic trading among a randomly selected group of investors from Gujarat.

4. RESEARCH OBJECTIVES

The present study has the following two objectives.

1. To study the level of awareness of investors towards algorithmic trading in Gujarat.
2. To examine the relationship between investor awareness and perception towards algorithmic trading in Gujarat.

Hypotheses of the Study

To test the objectives, the following null hypotheses were framed.

H01: The level of awareness of investors towards algorithmic trading is not significantly different from the neutral level (mean score of 3).

H02: There is no significant difference in the level of awareness between male and female investors.

H03: There is no significant difference in the level of awareness among investors of different age groups.

H04: There is no significant difference in the level of awareness among investors with different educational qualifications.

H05: There is no significant difference in the level of awareness among investors with different investing experience.

H06: There is no significant relationship between awareness and perception of investors towards algorithmic trading.

5. SAMPLE SIZE

The sample size of the study is 150 investors. This number was fixed after considering the time and cost of collecting data from four cities and the need to have enough respondents in each group for the statistical tests used. A sample of this size gives more than thirty respondents in most of the groups formed on the basis of gender, age, education and experience, which is the least number usually needed for tests such as the t test and ANOVA. (Rahat et al., 2023; Bunkar & Ramaiah, 2024).

Only those persons were included who have an active demat account and have bought or sold shares at least once. Out of the 150 respondents, 40 are from Ahmedabad, 43 from Surat, 38 from Vadodara and 29 from Rajkot.

6. SAMPLING TECHNIQUE

Simple random sampling was used to select the respondents. In this method, every investor in the list has an equal chance of being selected, and the selection does not depend on the choice of the researcher. This helps to reduce bias and makes it possible to apply the results to the larger group of investors.

First, a list of investors with active demat and trading accounts was prepared with the help of brokers, sub brokers and investor groups in Ahmedabad, Surat, Vadodara and Rajkot. Each name on the list was given a number. The respondents were then picked with the help of computer generated random numbers. If

a selected person was not available or did not wish to take part, the next random number was used in place of that person. The questionnaire was filled through personal meetings and through an online form sent to the selected persons.

7. DATA ANALYSIS

The primary data collected from the 150 respondents were entered into a spreadsheet, checked for errors and analysed with Python (SciPy) and Microsoft Excel. The tools used are descriptive statistics, Cronbach's alpha, one-sample t test, independent samples t test, one-way ANOVA with Tukey post hoc test, chi-square test, Pearson correlation and simple linear regression. All the tests were applied at the 5 per cent level of significance.

7.1 Research instrument

The data were collected with a structured questionnaire of three parts. Part A asked for the personal details of the respondent, namely gender, age, education, occupation, investing experience and city. Part B contained eight statements to measure awareness of algorithmic trading, and Part C contained ten statements to measure perception. The statements in Parts B and C were rated on a five-point Likert scale, where 1 means strongly disagree and 5 means strongly agree. The average of the statements was taken as the awareness score and the perception score of each respondent. A mean score below 2.50 was treated as low, a score from 2.50 to 3.49 as moderate, and a score of 3.50 and above as high.

The reliability of the scales was checked with Cronbach's alpha. The value was 0.880 for the awareness scale and 0.857 for the perception scale. Both are above the commonly accepted limit of 0.70, so the scales can be considered reliable.

7.2 Profile of the respondents

Table 1: Demographic profile of the respondents (N = 150)

Variable	Category	Frequency	Percentage
Gender	Male	106	70.7
	Female	44	29.3
Age group (years)	21-30	44	29.3
	31-40	54	36.0
	41-50	30	20.0
	Above 50	22	14.7
Education	Graduate	68	45.3
	Post graduate	54	36.0
	Professional / Other	28	18.7
Occupation	Salaried	51	34.0
	Business	50	33.3
	Professional	28	18.7
	Student / Others	21	14.0
Investing experience	Below 3 years	33	22.0
	3 to 5 years	51	34.0
	Above 5 years	66	44.0
City	Ahmedabad	40	26.7
	Surat	43	28.7
	Vadodara	38	25.3
	Rajkot	29	19.3

Source: *Primary data*

Table 1 shows that 70.7 per cent of the respondents are male and 29.3 per cent are female. The largest group by age is 31 to 40 years (36 per cent), followed by the group of 21 to 30 years (29.3 per cent). Graduates form the largest group by education (45.3 per cent), and 36 per cent hold a post graduate degree. Salaried persons (34 per cent) and businessmen (33.3 per cent) are almost equal in number. By experience, 44 per cent of the respondents have been investing for more than five years, while 22 per cent have less than three years of experience. The respondents are spread over the four cities, with Surat (28.7 per cent) and Ahmedabad (26.7 per cent) having the largest shares.

7.3 Objective 1: Level of awareness of investors towards algorithmic trading

7.3.1 Statement wise awareness

Table 2: Awareness of investors towards algorithmic trading

No.	Statement	Mean	SD	Level
1	I know the meaning of algorithmic trading.	3.51	0.83	High
2	I know that algorithmic trading places buy and sell orders automatically on the basis of set rules.	3.25	0.89	Moderate
3	I know that retail investors can use algorithmic trading through their brokers.	2.89	0.81	Moderate

4	I know that SEBI has made rules for algorithmic trading.	3.17	0.86	Moderate
5	I know that algorithmic strategies need approval and testing before they are used.	2.76	0.81	Moderate
6	I know that large institutions use algorithmic trading in the Indian stock market.	3.43	0.85	Moderate
7	I know the risks of algorithmic trading, such as system failure and wrong coding.	2.68	0.89	Moderate
8	I know the difference between algorithmic trading and normal manual trading.	3.03	0.85	Moderate
	Overall awareness score	**3.09**	**0.63**	**Moderate**

Source: *Primary data. Scale: 1 = strongly disagree, 5 = strongly agree.*

Table 2 shows that the mean scores of the awareness statements range from 2.68 to 3.51. The highest score (3.51) is for knowing the meaning of algorithmic trading, which is the only statement in the high group. The second highest score (3.43) is for knowing that large institutions use algorithmic trading in the Indian market. The lowest scores are for knowing the risks of algorithmic trading (2.68), knowing that strategies need approval and testing (2.76) and knowing that retail investors can use algorithmic trading through their brokers (2.89). This means that investors have a general idea of what algorithmic trading is, but they know much less about how it can be used by an ordinary investor and what the risks and rules are.

7.3.2 Overall level of awareness

The overall awareness score of the respondents is 3.09 with a standard deviation of 0.63, which falls in the moderate group. To test H01, a one-sample t test was applied with the neutral value of 3 as the test value. The result is $t(149) = 1.74$, $p = 0.084$. As the p value is more than 0.05, the null hypothesis is not rejected. This means that the awareness of the investors is not significantly different from the neutral level; in other words, investors are neither well aware nor unaware of algorithmic trading, and their knowledge is at a middle level.

Table 3: Distribution of respondents by level of awareness

Level of awareness	Score range	Number of respondents	Percentage
Low	Below 2.50	19	12.7
Moderate	2.50 to 3.49	96	64.0
High	3.50 and above	35	23.3

Source: *Primary data*

Table 3 shows that 96 respondents (64.0 per cent) have a moderate level of awareness, 35 respondents (23.3 per cent) have a high level and 19 respondents (12.7 per cent) have a low level. Nearly two out of three investors are therefore in the middle group, and less than one fourth can be called well aware.

7.3.3 Awareness across groups of investors

To find out whether awareness differs among different types of investors, the independent samples t test was used for gender and one-way ANOVA was used for age group, education and investing experience. The results are given in Table 4.

Table 4: Awareness score across groups of investors

Variable	Group	n	Mean	SD	Test statistic	p value	Result
Gender	Male	106	3.13	0.68	$t = 1.23$ (df = 148)	0.221	Not significant
	Female	44	2.99	0.47			
Age group	21-30	44	3.08	0.71	$F = 0.74$ (df = 3, 146)	0.528	Not significant
	31-40	54	3.01	0.53			
	41-50	30	3.15	0.69			
	Above 50	22	3.23	0.59			
Education	Graduate	68	2.97	0.59	$F = 2.31$ (df = 2, 147)	0.102	Not significant
	Post graduate	54	3.21	0.59			
	Professional / Other	28	3.14	0.75			
Experience	Below 3 years	33	2.84	0.54	$F = 6.25$ (df = 2, 147)	0.002	Significant

	3 to 5 years	51	3.01	0.58			
	Above 5 years	66	3.27	0.65			

Source: *Primary data. Significance at the 5 per cent level.*

The mean awareness score of male investors (3.13) is slightly higher than that of female investors (2.99), but the difference is not significant, $t(148) = 1.23$, $p = 0.221$. Hence H02 is not rejected. In the same way, the differences among the age groups, $F(3, 146) = 0.74$, $p = 0.528$, and among the education groups, $F(2, 147) = 2.31$, $p = 0.102$, are not significant, so H03 and H04 are not rejected. Post graduates have a somewhat higher mean (3.21) than graduates (2.97), but this difference is not large enough to be called significant at the 5 per cent level.

Investing experience, however, makes a clear difference, $F(2, 147) = 6.25$, $p = 0.002$. The awareness score rises from 2.84 for investors with less than three years of experience to 3.01 for those with three to five years and 3.27 for those with more than five years. The strength of this effect is small to medium (eta squared = 0.078), which means that experience explains about 7.8 per cent of the differences in awareness. The Tukey post hoc test shows that the difference between investors with less than three years and those with more than five years is significant ($p = 0.003$), while the other two pairs are not significant at the 5 per cent level (below three years and three to five years, $p = 0.392$; three to five years and above five years, $p = 0.062$). H05 is therefore rejected.

A chi-square test was also applied to see whether the level of awareness (low, moderate, high) is associated with investing experience. The result is shown in Table 5.

Table 5: Investing experience and level of awareness (number of respondents)

Investing experience	Low	Moderate	High	Total
Below 3 years	7	23	3	33
3 to 5 years	6	35	10	51
Above 5 years	6	38	22	66
Total	19	96	35	150

Source: *Primary data.*

The chi-square value is 9.37 with 4 degrees of freedom and $p = 0.053$. This is just above the 5 per cent level, so the association is not significant, although it is close to the limit. The table still shows a clear pattern: 22 of the 66 investors with more than five years of experience have a high level of awareness, compared with only 3 of the 33 investors with less than three years of experience. The ANOVA result and this pattern together suggest that experience in the market is the main factor that goes with higher awareness of algorithmic trading.

7.4 Objective 2: Relationship between awareness and perception

7.4.1 Perception of investors towards algorithmic trading

Table 6: Perception of investors towards algorithmic trading

No.	Statement	Mean	SD	Level
1	Algorithmic trading gives faster execution of orders.	3.62	0.80	High
2	Algorithmic trading reduces the effect of fear and greed on trading decisions.	3.56	0.85	High
3	Algorithmic trading can lower the cost of trading.	3.49	0.87	Moderate
4	Algorithmic trading helps an investor to follow a trading plan with discipline.	3.58	0.92	High
5	Algorithmic trading is a modern way of trading that will be used more in the future.	3.79	0.79	High
6	Algorithmic trading helps in handling many trades at the same time.	3.57	0.84	High
7	Algorithmic trading gives small investors a fair chance in the market.	3.35	0.90	Moderate
8	I trust the algorithmic trading platforms offered by registered brokers.	3.15	0.79	Moderate
9	The present SEBI rules are enough to protect investors in algorithmic trading.	3.19	0.88	Moderate
10	I would like to use algorithmic trading in the future.	3.45	0.86	Moderate
	Overall perception score	**3.48**	**0.56**	**Moderate**

Source: *Primary data. Scale: 1 = strongly disagree, 5 = strongly agree.*

The overall perception score is 3.48 (SD = 0.56), which is in the high group, and it is significantly above the neutral value of 3, $t(149) = 10.35$, $p < 0.001$. As Table 6 shows, the investors agree most with the statements that algorithmic trading is a modern way that will be used more in the future (3.79), that it gives faster execution (3.62), that it helps in following a trading plan with discipline (3.58) and that it can handle many trades at the same time (3.57). The lowest scores are for trust in the platforms of registered brokers (3.15) and for the belief that the present SEBI rules are enough (3.19). So the investors see the benefits of algorithmic trading, but they are less sure about trust and protection.

Table 7: Distribution of respondents by level of perception

Perception	Score range	Number of respondents	Percentage
Unfavourable	Below 2.50	5	3.3
Neutral	2.50 to 3.49	59	39.3
Favourable	3.50 and above	86	57.3

Source: *Primary data*

Table 7 shows that 86 respondents (57.3 per cent) have a favourable perception, 59 respondents (39.3 per cent) are neutral and only 5 respondents (3.3 per cent) have an unfavourable perception.

7.4.2 Correlation between awareness and perception

To test H06, the Pearson correlation coefficient was calculated between the awareness score and the perception score. The coefficient is $r = 0.58$ with $p < 0.001$. This shows a strong and significant positive relationship, which means that the investors who are more aware of algorithmic trading also have a more favourable perception of it. The null hypothesis H06 is rejected.

7.4.3 Regression of perception on awareness

A simple linear regression was run with perception as the dependent variable and awareness as the independent variable, to find how much of the perception can be explained by awareness. The results are given in Table 8.

Table 8: Simple linear regression of perception on awareness

Variable	B	Std. error	Beta	t value	p value
Constant	1.861	—	—	—	—
Awareness	0.523	0.060	0.582	8.72	< 0.001

Source: *Primary data. $R^2 = 0.339$, adjusted $R^2 = 0.335$, $F(1, 148) = 76.00$, $p < 0.001$.*

The regression model is significant, $F(1, 148) = 76.00$, $p < 0.001$, and the value of R^2 is 0.339. This means that awareness alone explains about 33.9 per cent of the variation in the perception of investors towards algorithmic trading. The regression equation is: Perception = 1.861 + 0.523 × Awareness. The coefficient of awareness ($B = 0.523$, $t = 8.72$, $p < 0.001$) shows that when the awareness score goes up by one point, the perception score goes up by about 0.52 points. The remaining part of the variation is likely to be due to other factors such as trust, past experience of losses and gains, and the influence of friends and brokers, which were not measured in this study.

The perception score was also compared across the three experience groups with one-way ANOVA, and no significant difference was found, $F(2, 147) = 1.99$, $p = 0.140$. This indicates that the favourable view of algorithmic trading is common to all experience groups, while the level of awareness is what differs with experience.

7.5 Summary of hypotheses testing

Table 9: Summary of hypotheses testing

Hypothesis	Statistical test	Test result	Decision
H01	One-sample t test	*t = 1.74, p = 0.084*	Not rejected
H02	Independent samples t test	*t = 1.23, p = 0.221*	Not rejected
H03	One-way ANOVA	*F = 0.74, p = 0.528*	Not rejected
H04	One-way ANOVA	*F = 2.31, p = 0.102*	Not rejected
H05	One-way ANOVA	*F = 6.25, p = 0.002*	Rejected
H06	Pearson correlation and regression	*r = 0.58, p < 0.001*	Rejected

Source: *Primary data. Level of significance = 0.05.*

8. CONCLUSION

8.1 Major findings

The study was carried out to find out the level of awareness of investors of Gujarat towards algorithmic trading and to see how this awareness is related to their perception. Primary data from 150 investors of Ahmedabad, Surat, Vadodara and Rajkot, selected by simple random sampling, were analysed with suitable statistical tools. The questionnaire was found to be reliable, with Cronbach's alpha values of 0.880 for awareness and 0.857 for perception.

With regard to the first objective, the investors were found to have a moderate level of awareness (mean = 3.09, SD = 0.63). About 64 per cent of the respondents fall in the moderate group, 23 per cent in the high group and 13 per cent in the low group. The investors know the meaning of algorithmic trading and know that large institutions use it, but they know much less about the use of algorithmic trading by retail investors, the approval and testing of strategies, and the risks involved. Awareness did not differ significantly with gender, age group or education, but it was significantly higher among investors with more than five years of experience than among those with less than three years of experience.

With regard to the second objective, the investors were found to have a favourable perception of algorithmic trading (mean = 3.48, SD = 0.56), and awareness was found to have a strong positive relationship with perception ($r = 0.58$, $p < 0.001$). Awareness alone explained about 33.9 per cent of the variation in perception, and each one point rise in the awareness score was linked with a rise of about 0.52 points in the perception score. The investors were more positive about the speed, discipline and future of algorithmic trading, and less positive about trust in platforms and the adequacy of the present SEBI rules.

8.2 Suggestions

Based on the findings, a few suggestions can be made. Brokers and exchanges should run short and simple awareness programmes for investors, especially for those with less than three years of experience, who showed the lowest awareness. These programmes should explain in plain language what algorithmic trading is, how a retail investor can use it through a registered broker, and what the risks are. Demonstration or practice accounts can help investors to understand the process without risking money.

The results show that the weakest areas of awareness are the approval and testing of strategies and the risks of algorithmic trading. SEBI and the exchanges can give more attention to these points in their investor education material. Investors should also be told clearly to use only the platforms of registered brokers and to be careful about sellers who promise sure or very high returns. Since trust in platforms and confidence in the existing rules were among the lower scoring items, clear and open information about safety measures can help to build trust that is based on knowledge.

Financial technology firms can use the strong link between awareness and perception in their own planning. Spending effort on education of the customer is likely to improve how the service is viewed, and this can in turn raise the willingness to use it.

8.3 Limitations and scope for future research

The study has some limitations. The sample is limited to 150 investors from four cities, so the results may not be the same for small towns and rural areas of Gujarat. The study depends on the opinions that the respondents gave in the questionnaire, which may differ from their real behaviour. Awareness was measured through self-reported knowledge and not through a test of actual knowledge. The sampling list was prepared with the help of brokers and investor groups, and investors who are not covered in such lists did not get a chance to be selected. Further, the study covers only awareness and perception and does not measure the actual use of algorithmic trading.

Future research can use a larger sample from more districts, include factors such as trust, perceived risk and financial literacy, and use methods such as structural equation modelling to study how these factors work together. A comparison between users and non-users of algorithmic trading, or a study of the same investors over time, can also give useful results.

To conclude, the investors of Gujarat have a moderate level of awareness and a favourable view of algorithmic trading, and the two go together. Better awareness is linked with a better perception. As algorithmic trading becomes available to more retail investors, making sure that their knowledge grows at the same pace will help them to use it safely and with confidence.

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