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"Preferences in Algorithmic Trading: Current Practices and Future Innovations"

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ABSTRACT:

Introduction

Algorithmic trading is a process that involves executing a large number of orders using electronically automated and pre-programmed trading instructions. These instructions account for various factors such as price, timing, and volume. The study aims to explore the impact and preferences for algorithmic trading among investors.

Objectives

- To understand the operational processes and mechanics of algorithmic trading.
- To assess the reasons for the preference for algorithmic trading among investors.
- To analyse the impact of demographic variables on the frequency of trading and awareness of algorithmic trading.

Research Methodology

The research utilized a descriptive research design. Data collection was conducted through questionnaires and interviews. A non-probability sampling method was employed, and responses were gathered from 124 participants in Ahmedabad.

Findings

- Algorithmic trading allows investors to use predefined strategies or create their own, which is a key factor in its preference.
- The study found that algorithmic trading is preferred due to its reduced human error and perceived safety.
- It was revealed that 55% of individuals are aware of algorithmic trading.
- Demographic variables were found to have a 34% impact on the frequency of trades conducted using algorithmic trading and a 29.2% impact on the awareness of algorithmic trading.
- The research indicates that investors are likely to prefer algorithmic trading in the future due to its safety, security, and the availability of various trading strategies.

INTRODUCTION:

Algorithmic trading refers to the process of executing a large number of orders using electronically automated, pre-programmed computer-generated trading instructions that account for variables such as price, timing, and volume. Essentially, an algorithm is a set of instructions designed to solve a problem. In the context of trading, computer algorithms gradually send small portions of the full order to the market over time. This method not only reduces transaction costs but also enables investment managers to have greater control over their trading processes.

Algorithmic trading is a specialized form of trading that encompasses computerized logic from the decision-making stage to transaction execution. This approach gained popularity following technological advancements that revolutionized asset trading. It involves using software and computers to generate and execute large orders in markets with electronic access. The orders typically originate from institutional investors, funds, and trading desks of major banks and brokers.

Algorithmic trading, also known as computer-directed trading, significantly cuts down transaction costs and empowers investment managers to manage their trading processes. The primary objective of algorithmic trading is not necessarily to maximize profits but to control execution costs and manage market risk.

Algorithms have become so integral to the trading landscape that it is inconceivable for a broker not to offer them, as clients now expect this service. These mathematical models analyze every quote and trade in the stock market, identify liquidity opportunities, and convert this information into intelligent trading decisions.

Algorithmic trading (algo trading) works by using computer algorithms to automate trading decisions based on predefined criteria. These algorithms analyze market data in real-time and execute trades faster than any human trader could.

LITERATURE REVIEW:

1. **Arora, G., & Sherry, A. M. (n.d.)** conducted a study titled "Evolution of Algo Trading and Its Future in India," which aimed to investigate the development and current state of algorithmic trading in India. This research included a comprehensive literature review to identify gaps in existing research. Using monthly data from the SEBI Handbook of Statistics (2016), spanning April 2010 to December 2016, the study found that in India, algorithmic trading orders, particularly in the cash segment, are executed at faster speeds, resulting in more trades compared to non-algorithmic orders. The large volume of orders placed by algorithmic trading contributes to substantial margins. Algorithmic trading is seen as a move towards a more transparent system and suggests lower leverage costs. The rapid growth of algorithmic trading indicates that India is progressing towards a more efficient capital market.

2. **Ramkumar, G. (2018)** conducted a study on the significance of algorithmic trading in the Indian stock market. The study aimed to understand the mechanism of algorithmic trading, identify reasons for its preference, understand its benefits for the stock market, and identify challenges in adopting it in India. The study sampled 50 respondents with sufficient knowledge of algorithmic trading. It concluded that algorithmic trading is an emerging strategy in the stock market and proves to be a better strategy for large trade volumes, benefiting investors. However, retail investors are concerned about being deprived of profits. SEBI has regulated such trading to ensure all types of investors benefit, avoiding inequalities among them.

3. **Hendershott, T., & Riordan, R. (2013)** examined algorithmic trading and the market for liquidity. The study found that algorithmic traders provide liquidity when it's expensive and consume it when it's cheap. They closely monitor the market and respond quickly to changing conditions. When spreads are narrow, algorithmic traders are less likely to submit new orders, cancel their orders, and are more likely to initiate trades. The study explores specific types of algorithmic trading strategies and their implications for academics, regulators, and market operators. It highlights the challenges slower traders face due to adverse selection, as faster traders are better informed about market conditions. The study suggests that increasing algorithmic trading could reduce liquidity and welfare, with significant applications for regulators and trading platform designers. The market infrastructure should ensure equal access for all participants to reduce costs.

4. **Yadav, Y. (2015**) investigated the impact of algorithmic trading on capital market efficiency. The study found that although algorithmic trading offers certain advantages, it also incurs substantial costs to the primary function of securities markets, which is to efficiently allocate capital throughout the real economy. The pervasive model risks and the pressures faced by informed investors can lead to a bias in favour of short-term, easily processed information. The study emphasizes the need for further consideration of the central role of securities prices in regulation and strategies to enhance market informativeness. As markets become more automated, addressing this issue is crucial for regulators.

OBJECTIVES:

1. To understand the mechanism of Algo trading.
2. To know the reasons for preferring algorithmic trading among the investors.
3. To study the benefits of algorithmic trading for equity, commodity and derivative stock market.
4. To study the awareness of algo trading among the investors.
5. To know the preferences and future scope of algo-trading.

RESEARCH METHODOLOGY:

RESEARCH DESIGN: Descriptive research design

POPULATION: Investors

SAMPLING FRAME: Ahmedabad

SAMPLING METHOD: Non-probability Convenience Sampling.

SAMPLING SIZE: 124 Sample Size

DATA COLLECTION METHOD:

Primary data : Through Interviews and Questionnaire.

Secondary Data: Through Books, Journals, Magazines, Various Articles, Annual Reports

CHI-SQUARE TEST

Demographic details with risk bearing capacity.

Relationship between gender and risk bearing capacity:

H0: There is no significance association between gender and risk bearing capacity.

H1: There is significance association between gender and risk bearing capacity.

Chi-Square Tests

	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.439[a]	3	.329
Likelihood Ratio	3.186	3	.364
Linear-by-Linear Association	.853	1	.356
N of Valid Cases	124		

a. 1 cells (12.5%) have expected count less than 5. The minimum expected count is 4.14.

Interpretation:

Above table shows that significant value is 0.329 which is more than 0.05. So alternate hypothesis is rejected and null hypothesis is accepted. Therefore, here is no significance association between gender and risk bearing capacity

Relationship between age and risk bearing capacity:

H0: There is no significance association between age and risk bearing capacity.

H1: There is significance association between age and risk bearing capacity.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	25.713[a]	9	.002

Likelihood Ratio	27.306	9	.001
Linear-by-Linear Association	.529	1	.467
N of Valid Cases	124		

a. 6 cells (37.5%) have expected count less than 5. The minimum expected count is 1.07.

Interpretation:

Above table shows that significant value is 0.002 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, here is significance association between age and risk bearing capacity.

Relationship between annual income and risk bearing capacity:

H0: There is no significance association between annual income and risk bearing capacity.

H1: There is significance association between annual income and risk bearing capacity.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	47.942[a]	12	.000
Likelihood Ratio	44.551	12	.000
Linear-by-Linear Association	1.671	1	.196
N of Valid Cases	124		

a. 9 cells (45.0%) have expected count less than 5. The minimum expected count is .92.

Interpretation:

Above table shows that significant value is 0.000 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, here is significance association between annual income and risk bearing capacity.

Relationship between occupation and risk bearing capacity:

H0: There is no significance association between occupation and risk bearing capacity.

H1: There is significance association between occupation and risk bearing capacity.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	55.379[a]	12	.000
Likelihood Ratio	56.956	12	.000
Linear-by-Linear Association	2.427	1	.119
N of Valid Cases	124		

a. 8 cells (40.0%) have expected count less than 5. The minimum expected count is .77.

Interpretation:

Above table shows that significant value is 0.000 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, here is significance association between occupation and risk bearing capacity.

Relationship between gender and frequency of trade:

H0: There is no significance association between gender and Frequency of trade.

H1: There is significance association between gender and frequency of trade.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	11.772[a]	6	.067
Likelihood Ratio	10.850	6	.093
Linear-by-Linear Association	.181	1	.671
N of Valid Cases	124		

a. 8 cells (57.1%) have expected count less than 5. The minimum expected count is .44.

Interpretation:

Above table shows that significant value is 0.067 which is more than 0.05. So alternate hypothesis is rejected and null hypothesis is accepted. Therefore, there is no significance association between gender and frequency of trade.

Relationship between age and frequency of trade:

H0: There is no significance association between age and Frequency of trade.

H1: There is significance association between age and frequency of trade.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	35.202[a]	18	.009
Likelihood Ratio	35.938	18	.007
Linear-by-Linear Association	6.255	1	.012
N of Valid Cases	124		

a. 17 cells (60.7%) have expected count less than 5. The minimum expected count is .11.

Interpretation:

Above table shows that significant value is 0.009 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, there is no significance association between age and frequency of trade.

Relationship between annual income and frequency of trade:

H0: There is no significance association between annual income and Frequency of trade.

H1: There is significance association between annual income and frequency of trade.

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Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	83.557[a]	24	.000
Likelihood Ratio	78.441	24	.000
Linear-by-Linear Association	13.906	1	.000
N of Valid Cases	124		

a. 26 cells (74.3%) have expected count less than 5. The minimum expected count is .10.

Interpretation:

Above table shows that significant value is 0.000 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, there is no significance association between annual income and frequency of trade.

Relationship between occupation and frequency of trade:

H0: There is no significance association between occupation and Frequency of trade.

H1: There is significance association between occupation and frequency of trade.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	56.094[a]	24	.000
Likelihood Ratio	57.915	24	.000
Linear-by-Linear Association	1.558	1	.212
N of Valid Cases	124		

a. 25 cells (71.4%) have expected count less than 5. The minimum expected count is .08.

Interpretation:

Above table shows that significant value is 0.000 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, there is no significance association between annual income and frequency of trade.

Relationship between gender and Awareness of various strategies:

H0: There is no significance association between gender and awareness of various strategies.

H1: There is significance association between gender and awareness of various strategies.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	7.070[a]	2	.029

Likelihood Ratio	6.204	2	.045
Linear-by-Linear Association	1.186	1	.276
N of Valid Cases	124		

a. 1 cells (16.7%) have expected count less than 5. The minimum expected count is 2.61.

Interpretation:

Above table shows that significant value is 0.029 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, there is no significance association between gender and awareness of various strategies.

Relationship between age and Awareness of various strategies:

H0: There is no significance association between age and awareness of various strategies

H1: There is significance association between age and awareness of various strategies.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	35.313[a]	6	.000
Likelihood Ratio	36.609	6	.000
Linear-by-Linear Association	15.490	1	.000
N of Valid Cases	124		

a. 6 cells (50.0%) have expected count less than 5. The minimum expected count is .68.

Interpretation:

Above table shows that significant value is 0.000 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, there is no significance association between gender and awareness of various strategies.

Relationship between annual income and Awareness of various strategies:

H0: There is no significance association between annual income and awareness of various strategies

H1: There is significance association between annual income and awareness of various strategies.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	26.366[a]	8	.001
Likelihood Ratio	28.858	8	.000
Linear-by-Linear Association	9.822	1	.002
N of Valid Cases	124		

a. 7 cells (46.7%) have expected count less than 5. The minimum expected count is .58.

Interpretation:

Above table shows that significant value is 0.001 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, there is no significance association between annual income and awareness of various strategies.

Relationship between occupation and Awareness of various strategies:

H0: There is no significance association between occupation and awareness of various strategies

H1: There is significance association between occupation and awareness of various strategies

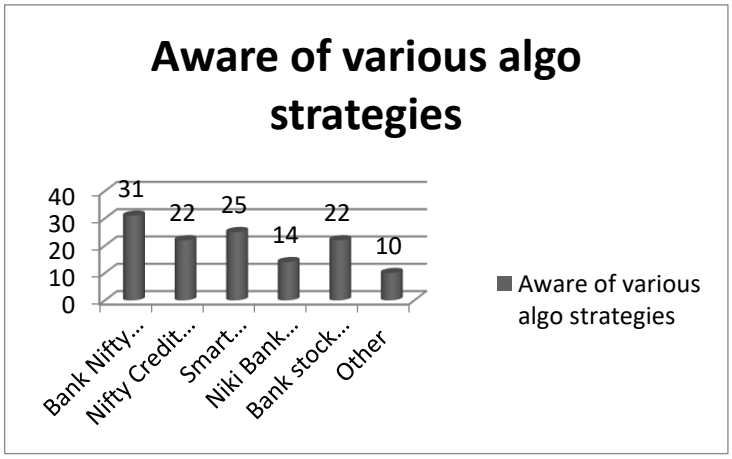
Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	33.356[a]	8	.000
Likelihood Ratio	35.427	8	.000
Linear-by-Linear Association	7.854	1	.005
N of Valid Cases	124		

a. 7 cells (46.7%) have expected count less than 5. The minimum expected count is .48.

Interpretation:

Above table shows that significant value is 0.000 which is less than 0.05. So null hypothesis is rejected and alternate hypothesis is accepted. Therefore, there is no significance association between occupation and awareness of various strategies.



Interpretation:

From the above table it can be concluded that 31 people prefer bank nifty crosswords, 22 people prefer nifty credit spread, 25 people prefer smart straddle, niki bank nifty is preferred by 14 people, 22 people uses bank stock option strategy, and 10 people prefer some other strategy.

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Non-parametric two or more independent sample test:

Before we have done Normality Test but our data was not normal that's why we have preferred to use Non-Parametric test.

Awareness of Algo trading with different age group:

H0: There is no significant difference between Awareness of Algo trading across different age group.

H1: There is a significant difference between Awareness of Algo trading across different age group.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Q19A. Aware_of_various_strategies_ available is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
2	The distribution of Q19B. Aware_that_can_make_own_ strategy is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of Q19C. Aware_about_the_risk is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
4	The distribution of Q19D. Aware_that_can_secure_position_ with_strict_stop_loss is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
5	The distribution of Q19E. Aware_that_it_has_less_human_ error is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
6	The distribution of Q19F. Aware_that_can_earn_more_profit comparatively is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Awareness of Algo trading with different annual income:

H0: There is no significant difference between Aware of Algo Trading with different annual income.

H1: There is a significant difference between Aware of algo trading with different annual income.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Q19A. Aware_of_various_strategies_ available is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.
2	The distribution of Q19B. Aware_that_can_make_own_ strategy is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.
3	The distribution of Q19C. Aware_about_the_risk is the same across categories of Q4. Annual_Income.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.
4	The distribution of Q19D. Aware_that_can_secure_position_ with_strict_stop_loss is the same across categories of Q4. Annual_Income.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.
5	The distribution of Q19E. Aware_that_it_has_less_human_ error is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
6	The distribution of Q19F. Aware_that_can_earn_more_profit comparatively is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.002	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

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Awareness of Algo trading with different occupation:

H0: There is no significant difference between Aware of various strategies available with different occupation.

H1: There is a significant difference between Aware of various strategies available with different occupation.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Q19A. Aware_of_various_strategies_ available is the same across categories of Q5.Occupation.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
2	The distribution of Q19B. Aware_that_can_make_own_ strategy is the same across categories of Q5.Occupation.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of Q19C. Aware_about_the_risk is the same across categories of Q5. Occupation.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
4	The distribution of Q19D. Aware_that_can_secure_position_ with_strict_stop_loss is the same across categories of Q5.Occupation.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
5	The distribution of Q19E. Aware_that_it_has_less_human_ error is the same across categories of Q5.Occupation.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
6	The distribution of Q19F. Aware_that_can_earn_more_profit comparatively is the same across categories of Q5.Occupation.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Preference of Algo trading with different age group:

H0: There is no significant difference between preferences of algo across different age groups

H1: There is a significant difference between preferences of algo across different age groups

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Q20A. Rate_the_following_factor_Less_ human_error is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
2	The distribution of Q20B. Rate_the_following_factor_High_ return is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of Q20C. Rate_the_following_factor_Low_risk is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
4	The distribution of Q20D. Rate_the_following_factor_Easy_ trade is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
5	The distribution of Q20E. Rate_the_following_factor_Earn_ more_profit is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
6	The distribution of Q20F. Rate_the_following_factor_Past_ experience is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
7	The distribution of Q20G. Rate_the_following_factor_Safety is the same across categories of Q3. Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
8	The distribution of Q20H. Rate_the_following_factor_ Simplicity is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
9	The distribution of Q20I. Rate_the_following_factor_ Affordability is the same across categories of Q3.Age.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

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Preference of Algo trading with annual income:

H0: There is no significant difference between preferences for algo trading across different income levels.

H1: There is a significant difference preferences for algo trading across different income levels.

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Q20A. Rate_the_following_factor_Less_ human_error is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
2	The distribution of Q20B. Rate_the_following_factor_High_ return is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of Q20C. Rate_the_following_factor_Low_risk is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
4	The distribution of Q20D. Rate_the_following_factor_Easy_ trade is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
5	The distribution of Q20E. Rate_the_following_factor_Earn_ more_profit is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
6	The distribution of Q20F. Rate_the_following_factor_Past_ experience is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
7	The distribution of Q20G. Rate_the_following_factor_Safety is the same across categories of Q4. Annual_Income.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
8	The distribution of Q20H. Rate_the_following_factor_ Simplicity is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.002	Reject the null hypothesis.
9	The distribution of Q20I. Rate_the_following_factor_ Affordability is the same across categories of Q4.Annual_Income.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

REGRESSION OF AWARENESS OF ALGORITHMIC TRADING:

Ho: There is no significant impact of Demographic variable on awareness of algo trading.

H1: There is no significant impact of Demographic variable on awareness of algo trading.

Variable:

DV: Awareness of algo among people.

IV: Demographic variables

Regression line= Awareness of algo trading+ (Gender), (Age), (Annual income), (Occupation).

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.292[a]	0.085	0.054	1.401	0.085	2.708	4	116	0.034	1.503

a. Predictors: (Constant), Q5.Occupation, Q2.Gender, Q3.Age, Q4.Annual_Income

b. Dependent Variable: Factor_average

Interpretation:

In the column labelled R are the values of the multiple correlation coefficients between the demographic variables and awareness of algo among people which is 0.292. The next column gives us a value of R2, which is a measure of demographic variable with awareness of algo among people. For the first model, its value is 0. 085, which means that Gender, Age, Annual income, Occupation, accounts for 8.5% of the variation in Are you aware of algorithmic trading.

The next column shows adjusted r value i.e. 0.054 which shows moderate positive relation.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.272	4	5.318	2.708	.034[b]
	Residual	227.836	116	1.964		
	Total	249.107	120			

a. Dependent Variable: Factor_average

b. Predictors: (Constant), Q5.Occupation, Q2.Gender, Q3.Age, Q4.Annual_Income

Interpretation:

The above table shows that the significance value is 0.034 which means it is less than 0.05, so null hypothesis is rejected and alternate hypothesis is accepted i.e. There is no significant impact of Demographic variable on awareness of algo trading.

REGRESSION WITH DEMOGRAPHIC VARIABLE ON FREQUENCY OF TRADE:

H0: There is no significant impact of demographic variables on frequency of trade.

H1: There is a significant impact of demographic variables on frequency of trade.

Variables:

DV: How frequently do you trade?

IP: All Demographics variables

Reg line: How frequently do you trade= A + B (Gender), (Age), (Annual income), (Occupation).

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.344[a]	0.118	0.089	1.446	0.118	3.994	4	119	0.004	2.086

a. Predictors: (Constant), Q5.Occupation, Q2.Gender, Q3.Age, Q4.Annual_Income

b. Dependent Variable: Q7.How_frequently_do_you_trade

Interpretation:

In the column labelled R are the values of the multiple correlation coefficients between the demographic variables with frequency of trade. The next column gives us a value of R2, which is a measure of relation of demographic variable with

frequency of trade. For the first model, its value is 0. 118, which means that Gender, Age, Annual income, Occupation, accounts for 11.8% of the variation in frequency of trade. The next column shows adjusted r value i.e. 0.089

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33.417	4	8.354	3.994	.004[b]
	Residual	248.930	119	2.092		
	Total	282.347	123			

a. Dependent Variable: Q7.How_frequently_do_you_trade

b. Predictors: (Constant), Q5.Occupation, Q2.Gender, Q3.Age, Q4.Annual_Income

Interpretation:

The above table shows that the significance value is 0.034 which means it is less than 0.05, so null hypothesis is rejected and alternate hypothesis is accepted i.e. There is no significant impact of Demographic variable on awareness of algo trading.

FINDINGS:

It is found that 55% of people are aware of algorithmic trading, as it tends to generate higher profits due to minimal manual errors. It is found that the majority of individuals interested in algorithmic trading come from business and job backgrounds. The study revealed that 85% of people are investing in the stock market. Most individuals aged 18-35 prefer algorithmic trading. A significant 84% of people trade in the stock market, with the majority engaging in daily trading. People's risk tolerance is moderate, with a preference to avoid taking excessive risks in the stock market. There are two types of trading: Intraday and Positional, with 75% of people engaging in positional trading. There is an equal likelihood of trading in the stock market independently or with the assistance of a trader or broker. About 84% of people have used algorithmic trading, and most of their trades were profitable. Financial advisors are the primary source of knowledge about algorithmic trading for most people. Algorithmic trading offers its own strategies, and users can also create their own strategies for trading. The preference for algorithmic trading is attributed to its lower human error rate and high safety. Algorithmic trading is favoured due to available strategies, reduced human error, lower risk, and the ability to create personal strategies. Investors are likely to prefer algorithmic trading in the future, viewing it as a safe and secure method that represents the future of trading. Demographic variables have a 34% impact on the frequency of trades using algorithmic trading. Demographic variables account for a 29.2% impact on the awareness of algorithmic trading.

CONCLUSION:

In this study we came to know that there are 55% of people who are aware of algorithmic trading. Through this study we came to understand the mechanism of algorithmic trading and how the trading is done in algo. We came to know that the main reason for preferring trading with algo is that it includes very less possibility of human error. The main reason for adopting algo trading is that there is no emotional errors included that prevents people from having loss. The investors feel that trading with algo is safe and there are various strategies that people can have for trading

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