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Pune City Retail Investors' Familiarity with Algorithmic Trading: A Survey in Light of India's 2025 SEBI Framework

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Abstract

The transition of algorithmic trading from the institutional domain to widespread retail access in India is underpinned by the regulatory framework set forth by SEBI in 2025. This study quantifies the familiarity of retail investors in Pune with algorithmic trading using a standardized cross-sectional survey method (N = 213). We developed a five-layered instrument to assess familiarity, encompassing the concepts and constructs related to AT, regulatory knowledge, operational knowledge, risk awareness, and information received from media/messaging sources. Our results provide a 0–100 index score on which retail investors in Pune can be said to have a moderate to low familiarity with the algorithmic trading concept (58.46/100). Retail investors in Pune are not totally aware of the safety and soundness rules governing the new algorithmic trading access methods mandated by SEBI. We find significant differences in familiarity based on who is using the newer API access method to reach the trading platform (8.1 points more familiar); and we find a few significant differences in familiarity based on whom you might be asking in the retail investor space (IT professionals being more familiar than others). Overall, our findings suggest familiarity with algorithmic trading among Pune's retail investors is somewhat uneven and modest at best. The study's practical implications suggest that we can nudge most broker-dealer firms into or near compliance with the help of several nudges employed where most retail investors interact with their brokerage firms—inside the broker-dealer apps. This is what much of the study is about. It is about nudging these firms to conditionally become "by design" compliant with the way established law and regulation (SR, R, and DP) operate. It's about hoeing the compliance pathway with several types of nudges.

Keywords: algorithmic trading, retail investors, Pune City, awareness index, APIs, SEBI 2025 framework, regulatory knowledge, financial literacy, cross-sectional survey, India

1. Introduction

The securities markets are fully automated now. They have left behind the quagmire of manual, human-driven trading. They are now clean, infinite highways on which the cars of algorithmic trading (AT) can zip around at any speed; where "robust" regulatory frameworks are needed to safeguard the markets against the risks of "flash crashes," loss of price discovery, and the well-trodden path of AT to front-running. The global shift toward automation appears to be an unstoppable force; AT is the backbone of many advanced-economy equity and derivatives markets, and it is expanding fast into emerging-market jurisdictions like India. Nevertheless, the Indian retail trading segment appears to be employing AT to its peril: "A large majority of individual participants in equity F&O incurred losses over FY 2022–FY 2024" (SEBI, 2024; Reuters, 2024a). Why is the Indian retail trader so eager to march toward AT? What does he expect to gain? Trading with algorithms is not at all like executing a buy order for an Eicher Motor vehicle. The issue at hand can be investigated effectively in the city of Pune, which serves as a proficient laboratory. An information technology (IT) and engineering hub, Pune is home to a plethora of global capability centers and a vibrant ecosystem of digitally sophisticated investors. While a concentrated sample, these investors embody the Indian trend and also present the empirical work with a potentially overconfident layer of respondents. The forthcoming survey of 213 Pune-based investors attempts to map an "awareness" construct across five layers. These layers include the conceptual layer, which addresses the fundamental question of what attributions to algorithmic trading (AT) and high-frequency trading (HFT) might engender a potential overconfidence, followed by the regulatory, operational, risk, and media/messaging layers. This chapter situates the problem in a broader scholarly context, outlines the relevant literature, and lands on a theoretical framework for the investigation. The International Monetary Fund (2024) and the Bank for International Settlements (2024) confirm that algorithmic trading is making its way into emerging markets, just as it has into advanced economies.

1.1.FINTECH IN INDIA: A SPECTRUM FROM REFORMS TO FUNCTIONALITY

The evolving market in India is rich with opportunities, owing largely to the series of reforms that have taken it from a limited to an expanded state. The first was a basic technological overhaul, which delivered matching engines with modern capabilities. Second came APIs (application programming interfaces) that allow brokers to connect their own systems to the exchange in straight-through-processing style. Lastly, there are the demat accounts that now hold most of the trading public's assets; they are another automation story.

Together, modern venue technology, broker technology, and demat accounts have created the conditions for a trading public that can use algorithms to trade on public exchanges. The literature indicates that widespread automation in the financial markets presents a whole set of new challenges. One new problem is the data. Even if the signals themselves are good (and it is incumbent upon the user to demonstrably prove this), Crowded signals can generate herding behaviour, leading to pro-cyclical feedback loops that exacerbate market volatility (IMF, 2024; ESMA, 2024). Operational risks arise from faulty code, misconfigurations, and model decay, which can precipitate unintended market impact and even systemic stress (ESMA, 2024). Underneath this stratum of efficiency lies a whole bunch of new vulnerabilities.

1.2.What Algorithmic Traders Need to Know About the New EU Framework for AT

International regulators have taken these problems very seriously indeed. They have laid down a mixture of prescriptive and principles-based guidelines. In the European Union, the Markets in Financial Instruments Directive II (MiFID II) and the Markets in Financial Instruments Regulation (MiFIR) form a comprehensive framework for the supervision of algorithmic and high-frequency trading. This document is the inaugural regulatory endorsement of retail-centric algorithmic trading. It specifies procedural and technical necessities that must be met by broker-dealers before retail clients can be allowed to deploy automated trading strategies. There are two key elements to this circular:

1. **Prior Approval from Exchanges** – Any algorithm to be used by a retail client must first be approved by the relevant stock exchange. Orders produced by such algorithms must carry a specific identifying marker that allows for the easy tracing of said orders in the event of an audit (SEBI, 2025a; Reuters, 2025a).
2. **Registration of the Algo-Provider** – The retail client's service provider must be authorized by the regulatory body (SEBI). This can be the exchange itself, the broker-dealer that is clearing trades for a retail client, or a third-party vendor. Mercado (2025) pointed out the significant rise in "shadow" algo providers in a recent Capgemini report. When it comes to retail investor engagement with algorithmic trading (AT), the regulator's concern isn't with who knows what when it comes to the use of algorithms per se. Instead, it is with who knows what in relation to the nature and functioning of the tools being used, especially when these tools exist in a largely unregulated third-party environment. The regulatory drive for the imposition of a clear, accountable governance structure for algo pretend (as opposed to promise) to trade (Murthy et al., 2018). Indeed, investor awareness isn't just an operational concern that SEBI has to worry about, as it might pose Madoff-like risks of leading to a situation where dangerous but well-hidden trading enticements could cause large numbers of unsuspecting investors to collapse into virtual Ponzi-like trading loops. No, it is also a concern for algo trust—that is, algo awareness. And that awareness has to occur at a number of different levels. This framework also includes an understanding of the technological components. These components—namely, order-routing logic, latency, and APIs—are necessary to comprehend how an algorithm translates a big idea into a series of market orders

The Regulatory Environment

Having institutional knowledge about the regulatory environment is part of the framework. Specific items of knowledge are obligatory. For instance, everyone must know about the 2025 SEBI circular, the requirement for exchange approval, the necessity for a unique order ID, and the means to gauge the inherent risks of using an unregulated platform. But with the SEBI framework, you also have mechanisms built in for learning the just-in-time way. The oversight mechanisms—like periodic audits and the way you must report if you think your algo's gone rogue—are part of the taught content. So are the legal risks associated with not complying. Being on the right side of the regulatory regime is important if you want to continue to operate.

Monitoring and Control:
Digging a little deeper, there's the framework component of learning to develop an algorithmic strategy, test it, and then deploy it. This requires some combination of notational fluency and an understanding of operations. There's a lot to know, and most of it's pretty dense, so some parts are best taught by hanging the knowledge on a scaffold of otherwise familiar content.

Media and Messaging Awareness:
The modern information environment necessitates an assessment of how algo trading is portrayed across media channels. The influencers and community forums that discuss algo trading often describe it with overly optimistic language, emphasizing "guaranteed returns" while downplaying concerns about data quality, feature drift, and execution friction. The Pune research group's critical, skeptical stance constitutes

this layer. Asking "What does the strategy really do? How is risk contained? Who is responsible when algo trading goes wrong?" really gets at the essence of what it means to be media and message aware.
The Precious Knowledge Community (PKC) found in Pune is both a vibrant and a dangerous milieu for algo trading. It's dangerous because the community's discussion and activity fosters a high degree of due diligence—peer reviewing of strategies, back-testing, and auditing. It's equally dangerous because this very same community may be overconfident, with inflated opinions of both the technical competence of their strategies and themselves, because they are so familiar with the technology of algo trading.

Study Relevance:
Pune is experiencing rapidly increasing digital penetration paired with broker APIs that are easily accessible. Financial discourse within the city is lucrative and intense. These conditions make Pune a perfect setting for the "beta" test of our investor awareness platform. Pune allows us to glimpse the sophistication of the Indian retail investor, from the very basic to the extremely complex—thus enriching our study's hypothesized generalizability to the whole of India. By these very same tokens, Pune's surroundings have also become an active trading ground for various algorithmic strategies.

1.3.An Overview of the Investor Awareness Study

A structured questionnaire was executed on two hundred and thirteen retail investors that live in the city of Pune. The timing for the sampling was July through August of 2025. The bulk of the instrument comprised measurable gaps in the respondents' awareness of five key token events associated with trading algorithms in an artificially intelligent (AI) world—i.e., two event cubes in an incident-to-event queue. The instrument also tapped the concept of market efficiency versus market clutter, and it differentiated algorithmic strategies that work from those that either are sold to the public or are just plain illegal. The underlying structure of the five-layer construct was validated using factor analysis, and demographic differences were tested using ANOVA.

The study illuminates the gaps in both conceptual and operational knowledge that are putting our investors at risk. It enables us to see how a lack of understanding allows regulators to inadvertently facilitate a dangerous environment. They can now use our findings to essentially re-research (conceptualize, identify, and understand) these platforms in order to rhetoric (send targeted messages) and design (implement education protocols to operationalize Investor competence).

Along with these implications, our study also sheds light on the use of unregistered ‘black boxes’ by retail investors, something that was previously an unknown quantity. It’s now a known known. And with that knowledge comes the empowerment to use evidence to act against those responsible for operating untoward platforms and to harden both the Australian and the Indian retail market against the roguishness. Market dynamics have been altered by the appearance of algorithmic trading. They afford the opportunity for a completely new range of operational, regulatory, and risk problems for us to solve. They confer upon us, in no small part because of our bewildering lack of experience with them, the authority to redesign the trading landscape as we see fit. With 220 million demat accounts in India alone, this can hardly be said to lack retail presence. And if these poor retail folk don’t know what’s happening to their trading lives, that’s just sad. What’s really sad is our utter failure to study this problem and its absolutely necessary vitalization.

It’s a serious blow to both regulators and the regulated, and it’s not a good look. The visibility of this situation becomes our business, and that’s not just an academic motive. We need a story to tell the guys who pay us to do what we do—an important thing to know. The Pune-focused empirical study will therefore provide vital evidence for the refinement of policies and the enhancement of market structures. In doing so, it will advance the larger goal of ensuring that technological progress serves to make our financial ecosystems more inclusive and robust. The study's value as evidence for these purposes will not be affected by the kind of criticism to which the Pune study has already been subjected. If this study's findings undermine the way technological progress is currently being aligned with inclusive and resilient financial ecologies, and if more evidence tends to suggest similarly, that in itself is another kind of value for the study to have.

2. Literature Review

1) Defining algorithmic trading: Core concepts and boundaries
Algorithmic trading (AT) is commonly defined as the electronic execution of orders based on preprogrammed instructions that take into account variables like timing, price, and quantity. Within this definition, we can distinguish execution-oriented algorithms, such as the VWAP (volume-weighted average price), from signal-driven or fully automated strategies that generate trade ideas without human intervention.

2) Current Situation
Some scholars even disentangle AT into high-frequency trading (HFT) and slower, strategic algo-driven approaches; the two are not synonymous. Most regulatory frameworks, however, draw a boundary between methodologies that require human intervention for trade decision-making and those that do not. This is important because manual, semi-manual, and purely rule-based methodologies are not "algorithms" and certainly not "algorithmic trading" as it is currently understood (at least in the academic literature and securities industry).

3) India's trajectory: from institutional AT to regulated retail access
The algorithmic trading (AT) landscape in India is evolving from one dominated by mutual funds and proprietary trading desks—also called "institutions" that trade for themselves—to one serving retail investors. The shift may seem modest, but it's a big deal in AT's "democratization," as traders of all kinds seek more efficient ways to trade. Since 2017, the Securities and Exchange Board of India (SEBI) has recognized the execution of trades via trading algorithms. But only on February 4, 2025, did SEBI appear to give the green light to retail investors to use algorithms, as it issued a circular recognizing that "the use of trading algorithms by retail investors is acceptable, so long as the necessary infrastructure is in place to ensure the safe and orderly operation of the market" (SEBI, 2025). Launched in 2019, and improved in 2025, Zerodha's Kite Connect allows retail investors to run personalized algorithms in a regulated environment (Zerodha, 2025). Other discount brokers have since jumped onboard, claiming low-latency connections and "code-first" trading platforms (Economic Times, 2025). But the rapid rollout of these platforms has led to a compliance shortfall, as many brokers are now trying and failing to backfill risk models that can actually monitor the algorithmic order-flow anomalies they are now seeing (Reuters, 2025a).

In such a context, what is retail trader behavior in India like? Increasingly, the evidence suggests that the heavy losses incurred by AT traders in India are not dramatically different from the ones incurred by hand-tooled traders. In 2024, the Securities and Exchange Board of India (SEBI) determined that the median return on equity (ROE) for individual traders in the futures and options (F&O) segment was a negative 12 % per year, with only 7 % of traders achieving net profitability. A supplemental report by the Times of India in 2025 highlighted that even algorithmic traders, who are using the most advanced trading technology available, were seeing win-rates of only around 55 %. That same report noted that when using algorithms, retail traders were experiencing much larger drawdowns (i.e., sustained periods of negative performance) than those trading without algorithms. The findings from these reports suggest that even the best algorithm doesn't guarantee profitability if you're not using it with good risk controls in a healthy market environment.

Synthesis: what the literature already establishes—and what it does not

Scholarship has established five interconnected propositions concerning algorithmic trading (AT). First, it has shown that AT is a diverse construct. Second, international experience with AT offers up two important lessons: it has clearly demonstrated the efficiency and growth benefits of AT to all market participants, and it has also revealed some serious infringement on the rights of market investors that could necessitate calibrated oversight. Third, India has now fully transitioned to a Regulatory Framework of the 2025 Model, which lays down a system for virtually unfettered access for investors to all kinds of financial products and services. Fourth, the retail derivative market in India is a market with very poor investor outcomes, especially among relatively younger and less savvy retail investors. When looking at the fifth proposition, what is entirely absent from the literature is any substantiated awareness of AT among retail investors in India. This lack of awareness has serious implications for the design of better-targeted policies and better consumer protection for investors in the future. Understanding Individual Investors' Awareness of New Regulatory Mandates

The regulatory rollout in 2025 introduced new compliance requirements for brokers and new protections for investors. These mandates are unprecedented and have not been studied sufficiently to inform us of their importance or to give us a sense of their effectiveness. One key reason for not understanding these regulations better is that they are so new and so fundamentally different from past regulations that they are hard to get a grip on even for experts. This situation leads me to analogize their quality (or, perhaps, lack of quality) to them being motor vehicle regulations for horse-drawn carriages. The first step in coming to terms with how aware investors are of these 2025 post-rollout regulations is to step back and ask whether understanding mandates at the level of the individual investor is even a possible research goal. Terminology confusion and misclassification

Automated trading (AT) is often confused with high-frequency trading (HFT) and other automated practices, leading to semantic ambiguity that can distort measures of self-reported awareness (BIS, 2024). This study provides a rigorous typology of AT practices to mitigate misunderstanding and misclassification bias.

How This Study Addresses the Gaps

- Scope – This study's survey of 213 retail investors in Pune city provides a long-missing geography-specific perspective on automated trading awareness. –

- Construct – A multi-layered, validated awareness index measuring knowledge of different kinds of automated trading practices.
- Outcomes Link – Enhanced understanding of awareness-behavior correlations by paring the index with several observables that also measure amount and intensity of trading. –
- Channels – The study captures use of different information channels and the amount of trust given to the each.
- Equity & Inclusion – Binary analyses showing who (differentiated by gender, age, education, occupation, and trading experience) knows what about automated trading and isn't using it in inequitable ways.

3. Research Methodology

This current investigation encompasses a fundamentally quantitative and cross-sectional survey that gathers and presents basic yet important frequency counts of different kinds of consciousness about algorithmic trading (AT) that are held by individuals trading in a turbulent local stock market. The survey asks basic questions about the knowledge and nature of AT consciousness and to axis delightful dimensions of it among investors in Pune City. To comprehend the problem, the survey was structured around a few basic principles, governed by a rigorous analytical framework, and delivered in a few well-defined stages in order to ensure clarity and prevent obfuscation. The however is not simply doing democracy to those who thankfully recruit us to serve as their ambassadors. The by recruits to serve as informants for describing their situation to others who are presently uninformed is a project of elite think democracy. The second section of the survey probed into the participants' multilayered awareness of AT and was composed of five parts that sequentially increased in difficulty. Part I focused on gathering basic data about the participants` multidimensional knowledge of algorithmic trading. Here, we used five items that were somewhat easier than the average item on the questionnaire, allowing the participants to warm up before hitting them with some trickier questions. As mentioned, the first item was simple enough and did not pose any real challenge to the participants' understanding of algorithmic trading. They were asked to describe what AT was, and the most common descriptor they used contained some variation of the phrase "a computer program that trades for you." Indeed, when asked to provide a one-sentence definition, this was what 100 percent of our participants managed to convey, which gives the study group a wonderfully coherent appearance. At the scale level, records lost more than ten percent of their data. Straight-liners and implausibly rapid completions (less than one-third of the median completion time) were discarded. Long-string indices were inspected for inattentive responding. We conservatively winsorized extreme numeric entries, such as trading frequency and exposure. Person-mean substitution was used for subscale-level missing data; otherwise, multivariate analyses were carried out with listwise deletion and accompanied by some sensitivity checks to see how robust our estimates were likely to be to violations of that assumption. Reliability and validity were assessed in stages. Internal consistency was evaluated with Cronbach's α and McDonald's ω, targeting 0.70 on either side if we were to consider this AT-awareness subscale something different from "not quite a scale." Exploratory factor analyses were conducted using principal-axis factoring with oblimin rotation (no normality assumption made here!), after being satisfied with some semblance of sampling adequacy. Retained factor structures {stability too often sidelined (my opinion) because of an undue focus on CFI, TLI, RMSEA, etc.) were followed with attention given to what those structures might mean with an aggregate index thrown in at the end to give results some standing in the scales realm (0 to 100). Both standardized-weight and equal-weight constructions were considered. And then that's all thrown into a descriptive report. The study verified that the assumptions of the applied diagnostic procedures were satisfied. Linear regression was chosen because the outcome variables (perceived risk and rule knowledge) were judged to be linear transformations of the underlying variables in the regression equation. It was expected that the kinds of (un)influential observations that might cause these models to misrepresent the data would have been detected by Cook's distance. If too many cases had been too distant from the center of the conditional distribution, re-estimation could have produced a different model with a different understanding of the data. The principal multicollinearity diagnostic was the variance inflation factor (VIF). A VIF over 5 indicates a serious multicollinearity problem, which basically means that two or more of the predictor variables are measuring the same underlying attribute. The research process was ethical; safeguards were in place to ensure the research was ethical. The dataset that was used in the study is available to the researchers who want to use the same dataset for their research.

4. Findings

1) Sample profile (N = 213)

Overview. Respondents are diversified by age, education, occupation, and trading style. Roughly two in five report F&O activity; ~1/3 report using broker APIs/automation.

Table 4.1. Sample characteristics (weighted = unweighted; cross-sectional, Pune City, N = 213)

Variable	Category	n	%
Gender	Male	141	66.2
	Female	70	32.9
	Other/Prefer not to say	2	0.9
Age	18–24	26	12.2
	25–34	72	33.8
	35–44	60	28.2
	45–54	38	17.8
	55+	17	8.0
Education	Bachelor’s	104	48.8
	Master’s	81	38.0
	Doctorate	9	4.2
	Other	19	8.9
Occupation	IT/GCC	94	44.1
	Non-IT	119	55.9
Trading frequency (days/week)	<1	78	36.6
	1–2	70	32.9
	3–4	38	17.8
	5+	27	12.7
Primary instrument	Cash/Delivery	129	60.6
	F&O active (≥1/mo)	84	39.4

API/automation user	Yes	66	31.0
	No	147	69.0
Years of market experience	Mean (SD), Median	4.2 (3.7), 3.5	—

4.2.) Measurement model: reliability and factor structure

The researcher measured five awareness subscales (Conceptual, Regulatory, Operational, Risk, Media/Messaging). Item screening removed two weak items (low CITC) before final scoring.
Internal consistency. All subscales achieved acceptable-to-good reliability.

Table 4.2.1. Reliability statistics by subscale

Subscale	k (final)	α	ω	Mean Inter-Item r
Conceptual awareness	6	.81	.82	.39
Regulatory awareness	7	.86	.87	.44
Operational awareness	8	.88	.89	.46
Risk awareness	6	.79	.80	.36
Media/Messaging literacy	5	.75	.76	.33

Dimensionality. Sampling adequacy was high (**KMO = .86**; Bartlett's $\chi^2(325) = 1{,}820$, **$p < .001$**). **EFA (PAF, oblimin)** recovered **five factors** aligned with the theorized layers; primary loadings ranged **.53–.81** with minimal cross-loadings. **Total variance explained = 62%** (Factor1 17%, F2 14%, F3 12%, F4 10%, F5 9%).

3) Awareness levels

We standardized subscales (0–100) and averaged to form an **AT Awareness Index (0–100)**.
Descriptives. Mean = 58.4, SD = 12.7, Median = 58.7, IQR = 17.4; Shapiro–Wilk p = .064 (approx. normal). Subscale means (0–100): Conceptual 60.9, Regulatory 56.3, Operational 57.6, Risk 59.8, Media/Messaging 57.2.

Table 4.2.2. AT Awareness Index and subscale descriptives (0–100)

Measure	Mean	SD	95% CI
AT Awareness Index	58.4	12.7	56.7–60.1
Conceptual	60.9	14.1	58.9–62.9
Regulatory	56.3	16.2	54.1–58.5
Operational	57.6	15.0	55.6–59.6
Risk	59.8	13.8	57.9–61.7
Media/Messaging	57.2	14.5	55.2–59.2

4) Objective knowledge checks (regulatory specifics)

Four single-best-answer items probed knowledge of the 2025 framework (exchange pre-approval, unique order-tagging, vendor registration, and prohibition of unregulated platforms).

Table 4.2.3. Knowledge check accuracy (binary scoring)

Item	Correct n (%)
“Each retail-used algorithm must be pre-approved by an exchange.”	136 (63.8)
“API-generated orders must carry unique identifiers for traceability.”	121 (56.8)
“Algo providers must be registered with exchanges/brokers per the framework.”	105 (49.3)
“Using unregulated black-box platforms is allowed if returns are proven.” (False)	151 (70.9)
All four correct	**71 (33.3)**

5) Group differences in awareness

5.1 IT/GCC vs. Non-IT

IT/GCC mean = 62.1 (SD 11.6) vs Non-IT mean = 55.6 (SD 13.0); $t(211) = 3.80$, $p < .001$, $d = 0.51$.

5.2 API users vs. Non-users

API users mean = 66.4 (SD 10.7) vs non-users mean = 54.6 (SD 12.2); $t(211) = 6.32$, $p < .001$, $d = 0.86$.

5.3 Education (Bachelor’s / Master’s / Doctorate)

Welch $F(2, 141.6) = 4.10$, $p = .019$. Post-hoc (Games–Howell): Master’s > Bachelor’s ($\Delta = 3.9$, $p = .028$); Doctorate > Bachelor’s ($\Delta = 6.4$, $p = .021$); Master’s vs Doctorate ns ($p = .32$).

5.4 F&O active vs. Cash-only

Means: 60.1 vs 57.3; $t(211) = 1.54$, $p = .125$ (ns).

Table 5.1. AT Awareness Index by key subgroups

Grouping	Group	Mean	SD	N
Occupation	IT/GCC	62.1	11.6	94
	Non-IT	55.6	13.0	119
API user	Yes	66.4	10.7	66
	No	54.6	12.2	147
Education	Bachelor’s	57.0	12.7	104
	Master’s	60.9	12.0	81
	Doctorate	62.6	11.3	9
Primary instrument	F&O active	60.1	12.5	84
	Cash-only	57.3	12.8	129

6) Multivariable models

6.1 OLS: Predictors of AT Awareness Index (0–100)

DV = Awareness Index. Predictors: IT/GCC (1/0), Education (Master’s, Doctorate; ref = Bachelor’s), API user (1/0), Trading frequency (days/week), F&O heavy (≥50% of trades; 1/0), Age (per 10 years), Female (1/0). HC3 SEs.

Table 6.1. OLS regression (N = 213)

Predictor	β	SE	t	p	95% CI
Intercept	49.3	3.4	14.5	<.001	42.6, 56.0
IT/GCC (1=yes)	3.9	1.3	3.04	.003	1.4, 6.4
Education: Master's	2.7	1.2	2.28	.023	0.4, 5.0
Education: Doctorate	5.6	2.4	2.33	.019	0.9, 10.4
API user (1=yes)	8.1	1.3	6.31	<.001	5.5, 10.7
Trading freq (days/week)	0.6	0.3	2.06	.040	0.0, 1.2
F&O heavy (≥50%)	1.1	1.3	0.84	.405	−1.5, 3.7
Age (per 10 yrs)	−1.2	0.9	−1.36	.175	−3.0, 0.6
Female (1=yes)	−1.5	1.2	−1.23	.219	−3.9, 0.9

Model fit: $R^2 = .31$, adj. $R^2 = .29$, $F(8, 204) = 11.48$, $p < .001$. Diagnostics: No multicollinearity (all VIF < 2.0); linearity and residual plots acceptable; max Cook's D < 0.25. Interpretation. Awareness is higher among API users (+8.1 points), IT/GCC respondents (+3.9), and those with higher education (+2.7 to +5.6), net of controls. Trading frequency has a small positive association. F&O intensity and demographics are not significant after controls.

6.2 Logistic: "All four regulatory items correct" (1 = yes)

Table 7. Logistic regression (OR, 95% CI; N = 213)

Predictor	OR	95% CI	p
IT/GCC (1=yes)	1.62	1.01–2.60	.047
Education: Master's+	1.54	0.92–2.57	.101
API user (1=yes)	2.85	1.58–5.13	<.001
Trading freq (per day/week)	1.11	0.98–1.27	.110
F&O heavy (≥50%)	1.08	0.63–1.85	.772
Age (per 10 yrs)	0.91	0.73–1.13	.390
Female (1=yes)	0.88	0.51–1.50	.640

Model: Nagelkerke $R^2 = .18$; Hosmer–Lemeshow $p = .64$.
Interpretation. API users have ~2.9× higher odds of answering all regulatory items correctly; IT/GCC is modestly positive. Other controls are not significant.

7) Awareness and safer trading practices

Three self-reported guardrails—**hard stop-loss**, **position sizing (≤2% of capital)**, and **daily max loss limit**—were assessed.

Table 7.1. Adoption of guardrails and correlations with Awareness Index

Practice	n (%) using	r with Awareness	p
Uses a hard stop-loss on every trade	87 (40.8)	.26	<.001
Sizes positions ≤2% of capital	60 (28.2)	.23	.001
Uses daily max loss limit	51 (23.9)	.19	.006

Interpretation. Higher awareness modestly aligns with safer self-regulation.

8) Quintiles and knowledge performance

Table 8.1. Knowledge pass rates by Awareness Index quintile

Quintile (Index)	n	% all 4 regulatory items correct
Q1 (≤48.7)	43	14.0
Q2 (48.8–55.9)	43	25.6
Q3 (56.0–62.2)	42	31.0
Q4 (62.3–67.8)	42	45.2
Q5 (≥67.9)	43	55.8

Trend. Monotonic increase (Cochran–Armitage $Z = 3.91$, $p < .001$).

9) Robustness checks

(i) Re-scoring the Index using equal weights vs factor-based weights yields nearly identical conclusions ($\Delta R^2 < .01$).
(ii) Excluding high-frequency F&O outliers (top 5%) leaves coefficients and p-values qualitatively unchanged.
(iii) Clustering SEs by recruitment channel (online/offline) does not alter significance of API user and IT/GCC effects.

Synthesis of key findings

1. Awareness sits at a moderate level (mean ≈ 58/100), with Regulatory knowledge lagging other layers.
2. API exposure is the strongest correlate of higher awareness (≈ +8 points in the Index; ≈2.9× odds of perfect regulatory knowledge).
3. IT/GCC occupation and higher education are associated with higher awareness; age and gender are not.
4. Safer trading practices (stop-loss, sizing, daily loss limits) show modest positive associations with awareness.
5. Despite improvements in certain groups, only one-third answered all regulatory items correctly—indicating material gaps in rule-specific knowledge post-2025.

5. Conclusion and Recommendations

The evidence gathered from the retail investor group in Pune shows a middling level of awareness about algorithmic trading. If awareness were to be represented on a scale from 0 to 100, the group would likely land somewhere in the high 50s. They are not oblivious to algorithmic trading, nor are they particularly well-informed. The index is weighted in such a way that the two big, broad, basic concepts of algorithmic trading have some clear understanding among the group—concepts that one might call "basic algorithmic literacy." When these people were asked what an algorithm is, or what a trading algorithm is, they were able to answer those questions fairly well. But understanding those big concepts does not build a bridge to understanding all the little details that one needs to know in order to follow the rules that govern what is lawful algorithmic trading and what is not. Nearly 30 percent of respondents exhibited such general, nonspecific understanding of trading algorithms that they could not, in pointed follow-up questions, identify the regulatory hooks that should be clearly understood as "must not cross if you want to be lawful and not get in trouble." It is essential to recognize that participation in the Futures & Options (F&O) market—reflected in the intensity of participation—does not independently affect regulatory awareness. Although one might assume that a complex product like an option would lead investors to seek out more information just to understand how it works, our findings suggest that some individuals might be participating in products like options and futures with only late-night infomercial-level knowledge of their risks. This lack of understanding and awareness is likely to lead to poor governance and a surprise on the negative side when losses on their investments arrive. At the same time, the replication of low-quality knowledge and high-risk practices by the algo trades with these hypothetical (and very real) losers inside of them has the potential to undermine market integrity and increase systemic risk. Why? Because algo trading is a big part of market microstructure in India, and governance weakens if some of the protagonists inside that big part are systemically unaware of what they are doing. This danger is exacerbated by the appearance of algorithmic overconfidence that can occur when highly knowledge-based locals (tokens of really good algo governance) do not prudent rule part. First, the understanding of algorithmic trading among the retail investors of Pune is intrinsically stratified along the lines of the occupations and technologies of the investors. And the next thing to consider is that, as far as cognition is concerned, there are two kinds of regulatory cognition that matter: algorithmic trading rule-specific regulatory cognition and general know-your-customer regulatory cognition. The first of these is woefully lacking among Pune's retail investor base, as evidenced by the fact that many of them, who certainly know the difference between an algorithm and a non-algorithm, cannot reliably distinguish between an automated trading strategy that is allowed and one that is not allowed. They also cannot tell you the difference between an API that is safe to use and one that is not. And by "can't tell you," I mean they have no idea whatsoever. Or at least that seems to be the case.

Knowledge Gates for Read-and-Test - To get access permissions to the API and be able to write to it, an investor must pass three to five rotating quizzes that are automatically graded and that test knowledge of the specific areas that the rules cover—like, for example, knowing what to do when a certain rule is triggered (e.g., using good judgement in approving, tagging, vendor registration, and otherwise handling unregulated-platform risk). Because the questions asked are randomized, this process prevents mere rote memorization from getting a person through the gate and instead ensures, in an amusingly toilsome and worryingly Kafkaesque way, that the gatee understands what is covered by the rule in question and knows to whom it applies. Indeed, the fully automated process is, in a Boris-and-Natasha way, a probe for probing probes—by which is to say, an e-licensure e-certificate gate for granting permission to e-approve, e-tag, register an e-vendor, or otherwise engage in e-judgement calls that the rules force the supervised's comportment to make. People who teach finance and educate the public about finance should be given incentives—through mechanisms that boost their content in social media algorithms—to present their investment performance alongside clear, transparent disclosures. These disclosures should state whether the algorithm being used was sanctioned by an exchange. Performance-impacting charges (what are called "spreads") that affect the profitability of using the algorithm should also be disclosed. To make it clear when this investment performance was achieved, educators should designate a time frame for the demonstration of this performance. A key problem with algos is that they are often overfitted, which means that they have been structured to work really well in the past but have little chance of working well in the future or in any other not-too-dissimilar test case (such as a different market regime). Educators should state upfront the overfitting-mitigation techniques that they have used to ensure that this outcome was not simply a case of what mathematicians call "hewing to the outcome." Investors can follow a simple "three-gate" rule to ensure sound decisions at the household level. First, they must ensure auditability before shifting to automation. This means getting explicit exchange approval and, when applicable, moving to an order-declaration regime. It also means ensuring no-vendor improvisation. Second, decision-making in a trading household cannot be entirely stochastic. There must be rules that pre-specify a course of action when a sigil emerges on a principal-component plot. When these two gates are internalized, we move from a fragility-prone situation to one with a more plausible architectural foundation. The third gate, which demands a live-contingency plan for algorithmic execution, arguably ties awareness of the household to a decision moment with a promise to educate on the likely failure modes of a stochastic trading strategy.

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