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RETAIL INVESTOR BOOM AND THE USE OF TECHNICAL ANALYSIS: A SYSTEMATIC REVIEW OF EMERGING MARKET EVIDENCE WITH FOCUS ON INDIA

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Abstract

Retail investors' engagement in Indian equity markets has increased substantially since 2020, but little is known about the extent to which this expansion depends on technical analysis (TA) and whether that reliance pays off. This paper evaluates the evidence on the expansion of retail investors and the use of TA in emerging markets, with India as the primary case. It seeks to record the magnitude of the boom, to synthesize knowledge regarding TA use and profitability, and to determine the conditions under which TA-driven retail trading succeeds or fails. This is a systematic review following the PRISMA guidelines on a selected corpus of 27 sources published between 1992 and 2026: 19 peer-reviewed papers, one working paper, five datasets from regulators or exchanges and two practitioner reports. Sources were classified thematically and triangulated with historical data on demat accounts, exchange investor registrations and Securities and Exchange Board of India (SEBI) examinations of derivatives trading. The number of demat accounts rose from around 5.5 crore in FY21 to 22.5 crore in FY26, whereas 87.7 to 91.1 per cent of individual derivatives traders lost money in each of FY24, FY25 and FY26. Rule-level TA tests are often supportive or conditional, while all user-level outcome studies reveal net losses. The study indicates that the weakness of TA in retail hands lies not in the indicators themselves but in how they are used: specifically the instrument, trading frequency, costs, behavioural bias and information sources. A framework and five testable propositions are proposed.

Keywords: retail investors; technical analysis; emerging markets; India; derivatives trading; systematic review

1. Introduction

Few changes in Indian finance over the last decade can match the rise of retail participation in the stock market. In late 2015, India had roughly 2.4 crore investor accounts on its two depositories [1]. By the end of FY26 NSDL and CDSL jointly had about 22.5 crore demat accounts, nearly four times the FY21 level of 5.5 crore [2]. As of 30 June 2026, the National Stock Exchange (NSE) had 13.24 crore unique registered investors and 26.14 crore registered trading accounts [3]. According to its own market report, over four in five registered investors joined after FY19 [4]. At the end of March 2026, individuals, directly and through mutual funds, held 18.7 per cent of the market capitalization of NSE-listed businesses, and mobile platforms now account for more than a fifth of cash-market turnover [5]. In a few years participation has expanded from a modest urban habit to a mainstream market activity.

This boom has brought with it a certain type of trading. Short-dated index options and equity derivatives in general have drawn very large numbers of individuals. SEBI [6] has described the level of trading in India's derivatives business, especially in index options, as very high when compared with other markets. SEBI's own profit-and-loss studies demonstrate that most people who trade in this segment lose money: 91.1 per cent in FY24 [7], over 91 per cent in FY25 [8] and 87.7 per cent in FY26 [9]. The loss share has not changed much even with the tightening of regulatory limits.

This type of trading goes hand in hand with technical analysis. TA looks at historical prices and volumes, sometimes using charts and indicators such as moving averages, the relative strength index (RSI) and Bollinger Bands, to time entries and exits. Under the efficient market hypothesis, such rules should earn nothing over and above compensation for risk [10]. The adaptive markets view admits that patterns may arise and disappear as conditions change [11]. TA is widely used by professionals. Survey evidence from fund managers in

several countries and from foreign-exchange dealers suggests that chart reading is a routine part of the toolkit, especially over short horizons [12], [13]. Whether rules make money is a separate and long-running debate: early tests on the Dow Jones index found that simple rules had real predictive content [14], while later surveys found that the picture was mixed and that profits tended to weaken in recent periods [15].

Two further facts frame the topic. First, the boom is directed. The SEBI Investor Survey 2025 found that 63 per cent of households know at least one securities-market product, but only 9.5 per cent, about 32.1 million households, actually invest, with urban participation at 15 per cent against 6 per cent in rural areas [16]. Second, the information environment has evolved. Free charting tools, trading apps and social media "fin-influencers" have reduced the cost of learning and using TA, not always for the better [17]. The time has come for a review which relates these developments to our knowledge of TA.

Throughout this paper three terms are used. A retail (or individual) investor is someone who buys or sells through a broker for his or her own account, as opposed to institutions and proprietary desks. Technical analysis is any trading methodology that is based primarily on past price and volume data. An emerging market is a market identified as such in the reviewed studies, and India is treated as the focus case.

The existing literature touches on the topic from three sides, and the sides rarely meet. The first is the TA profitability literature, which tests rules on index or stock series. Its emerging-market branch is mostly from the 1990s and 2000s [18], [19], [20], and its Indian branch tests rules on indices or large stocks without observing who actually trades [21], [22], [23]. The second is the retail-trading literature, which follows real accounts and finds that individuals lose from active trading [24], [25], [26], but which usually does not record whether TA was the method used. The third is the regulator and practitioner material from India, which documents the boom and the losses in detail [7], [9] yet observes outcomes, not methods.

Three things follow. There is no review that brings the boom, the use of TA and the trading outcomes into one frame for an emerging market. The rule-level and user-level evidence appear to point in different directions, and this apparent paradox has not been examined. And the Indian evidence on behaviour, such as the role of fear of missing out and herding [27], [28], has not been linked to the TA literature. The problem is made more pressing by timing: the Indian data have changed quickly, with SEBI's FY26 study published only in August 2026, so earlier syntheses are already out of date.

The question matters to several groups. Regulators need to know whether limits on contract size and expiries address the cause of retail losses or only its symptoms. Brokers and trading platforms need evidence on how charting tools and alerts shape behaviour, since they design the interfaces most investors use. Educators and financial-literacy programmes need to know what to teach: if the problem is how TA is used, then teaching indicators alone is not enough. Retail investors themselves gain from a clear statement of what the evidence says about profits, costs and persistence. Researchers gain a map of what has been tested and what has not.

The topic is also significant for emerging-market scholarship. The best-known evidence on retail losses comes from Taiwan [25], Brazil [26] and the United States [24], [29]. India now has the largest retail derivatives activity in the sample and the most detailed regulator data, which offers a new setting for testing ideas developed elsewhere.

The study has four objectives, each tied to a research question (RQ):

RO1: To document the scale, speed and composition of the retail boom in India (RQ1: How large and how fast has retail participation grown, and who is trading what?).

RO2: To synthesise evidence on the use of technical analysis by retail investors in emerging markets (RQ2: What is known about how widely and why retail investors use TA?).

RO3: To compare rule-level evidence on TA profitability with user-level evidence on retail outcomes (RQ3: Does TA earn money in tests, and do TA-using retail investors earn money in practice?).

RO4: To identify the conditions that separate success from failure and to propose a framework and research agenda (RQ4: Which moderators matter, and what should be tested next?).

The paper makes four contributions. It assembles in one place the historical data on India's retail boom and SEBI's derivatives-trader studies through FY26. It separates rule-level from user-level evidence on TA and shows that they have rarely been read together. It offers a framework that links enablers, TA adoption, trading behaviour, outcomes and regulatory feedback. Finally, it states five propositions and a research agenda that can be tested with account-level data.

The remainder of the paper is organised as follows. Section 2 reviews the literature and identifies the gap. Section 3 explains the review method. Section 4 reports the results, Section 5 discusses them and Section 6 concludes with limitations and future research.

2. Literature Review

The efficient market hypothesis holds that prices reflect available information, so that past prices cannot be used to earn excess returns [10]. The adaptive markets hypothesis softens this claim, arguing that efficiency varies with the population of traders and the market environment, so that a rule can work for a time and then stop [11]. On the behavioural side, prospect theory explains why investors weigh losses more heavily than equal gains [30], and the disposition effect describes the tendency to sell winners early and hold losers [31], [32]. These ideas matter here because they predict how retail traders may handle signals from any rule.

Profitability of TA in developed markets- Brock, Lakonishok and LeBaron tested moving-average and trading-range rules on the Dow Jones index over nearly a century and found returns that standard stochastic models could not reproduce [14]. Lo, Mamaysky and Wang developed an automated way of recognising chart patterns and found that some carried incremental information [33]. Park and Irwin surveyed the modern literature and reported that most studies found positive

results, but also that profits appeared to weaken in later periods and that data snooping was a frequent weakness [15]. More recently, Neely and co-authors showed that technical indicators help forecast the equity risk premium [34].

Emerging markets- Bessembinder and Chan found that simple rules had forecasting power in Asian stock markets, with stronger results in the less developed ones [18]. Ratner and Leal tested rules in emerging equity markets of Latin America and Asia and found significant returns in only a subset of markets [19]. Gunasekarage and Power examined moving-average rules in South Asian markets, including India, and reported predictive ability [20]. These studies treat the markets as candidates for inefficiency, which is the reason emerging markets have attracted so much TA research.

India- Mitra applied moving-average rules to four Indian stock indices and found that they captured the direction of price movement and gave significant positive returns, while warning that short-term rules trade often and so incur heavy transaction costs [21]. Muruganandan tested RSI and MACD rules on the BSE Sensex from February 2000 to May 2018 and split the sample into bull and bear phases. The RSI rule failed to deliver positive returns even before costs, while MACD sell signals did better than the unconditional mean in bear markets, though returns did not compensate for risk [22]. Tadas and co-authors tested three strategies on hourly prices of 14 large Nifty 50 stocks between January and August 2022 and found that a combined Bollinger Bands and RSI strategy beat buy-and-hold in 10 of the 14 stocks [23].

Who uses TA, and with what result- Surveys of fund managers across five countries show that TA is widely used, especially for short horizons [12], and a review of the foreign-exchange literature describes a lasting reliance on charts among dealers [13]. For individual investors, Hoffmann and Shefrin matched survey answers with the trading records of about 5,500 Dutch brokerage clients. Investors who said they used TA were more inclined towards short-term speculation, held more concentrated portfolios and earned lower returns, and the effect was strongest among frequent options traders [35].

Retail trading outcomes- Barber and Odean showed with US brokerage records that the households that traded most earned the lowest net returns [24]. Barber, Lee, Liu and Odean used complete Taiwanese data to show that individual investors as a group lose from trading while institutions gain [25]. Chague, De-Losso and Giovannetti followed every person who began day trading Brazilian equity futures between 2013 and 2015. Of those who persisted for more than 300 days, 97 per cent lost money, only 1.1 per cent earned more than the minimum wage, and the authors found no evidence of learning [26]. Barber and colleagues also found that attention-driven buying by users of a zero-commission app was followed by negative returns [29].

Behaviour and information in India- Two survey studies of Indian retail investors found that herding and loss aversion influence investment decisions and that fear of missing out strengthens these effects [27], [28]. On information sources, CFA Institute surveyed 1,615 Indian retail investors and reviewed the content of 51 prominent finfluencers, reporting that only about 2 per cent of the finfluencers were registered with SEBI and that 35 per cent of surveyed investors never verified an influencer's credentials before acting [17]. A follow-up review of 48 finfluencers across January to October 2025 found only partial progress: three were registered and a third gave explicit buy, hold or sell recommendations [36]. A case-based paper argues for stricter oversight [37].

Critical analysis of previous studies

Table 1 sets the main studies side by side. Three patterns stand out.

Table 1. Comparison of selected previous studies

Study	Market and data	Main finding	Limitation for this review
Brock et al. [14]	US; Dow Jones index, 1897–1986	Moving-average and range-break rules produced returns that simple stochastic models could not explain	Developed market; index-level; before the retail boom
Park & Irwin [15]	Survey of modern TA studies	Most studies positive, but profits weakened in later periods and data snooping was common	Mostly index and currency data; no retail user outcomes
Bessembinder & Chan [18]	Asian stock markets	Rules had forecasting power, stronger in less developed markets	Early-1990s data; no investor-level evidence
Ratner & Leal [19]	Emerging markets of Latin America and Asia	Significant returns in only a subset of markets	Pre-2000 data; cost treatment varies
Gunasekarage & Power [20]	South Asian markets, including India; moving-average rules	Rules showed predictive ability	Index-level; no retail cohort
Mitra [21]	Four Indian stock indices	Positive returns from moving-average rules, but excessive trading adds costs	Index-level; before the boom
Muruganandan [22]	BSE Sensex, 2000–2018; RSI and MACD	RSI failed; MACD sell signals did better in bear phases; no risk compensation	Ends in 2018; index-level

Study	Market and data	Main finding	Limitation for this review
Tadas et al. [23]	14 Nifty 50 stocks, hourly, Jan–Aug 2022	Bollinger–RSI method beat buy-and-hold in 10 of 14 stocks	Eight-month window; simulated trades, not real investors
Hoffmann & Shefrin [35]	About 5,500 Dutch brokerage clients, 2000–2006	TA users earned lower returns; effect largest among frequent options traders	Developed market; pre-app era
Chague et al. [26]	Brazil; day traders in equity futures, 2013–2015	97% of persistent day traders lost money; no learning	Futures day trading; TA use not observed
SEBI research [7], [9]	India; retail F&O traders, FY22–FY26	87.7–93% of traders lost money; losses larger for small holdings	Observed outcomes; method (TA) not observed

First, the user-level studies and the rule-level studies answer different questions. The former ask whether a rule applied mechanically to a price series makes money. The latter ask whether people who trade actively, using TA or not, make money. The answers at the rule level are mostly affirmative or conditional, while the user-level answers are all negative. Second, the TA studies of emerging markets are old. Their data cut off well before the boom of 2020, so they say little about a population that is younger, trades through apps and favours options. Third, even the latest Indian rule test covers just eight months of data for large stocks [23]. Regulator data cannot tell whether TA was used.

There are strengths to keep. The nearest available test of whether TA users do worse is the matched survey-and-trading approach of Hoffmann and Shefrin [35]. The full-population methodology of Chague and colleagues overcomes survivorship concerns [26]. SEBI's research has the biggest account-level sample for any emerging market, with breakdowns by age, income and portfolio size [7], [38].

Finding the research gap

Five gaps may be identified from this comparison.

G1. Adoption without measure**.** The corpus does not directly measure the usage of TA by Indian retail investors, but infers use from platform attributes, surveys of other populations and trading style.

G2. Rule-level and user-level evidence have not been harmonised. No one has looked at why rules can seem profitable in theory while the people who trade actively lose.

G3. The post-2020 cohort remains little investigated. The existing emerging-market TA studies are pre-boom, and the only Indian test with 2022 data is short [23].

G4. TA tests do not incorporate instrument and cost effects. Tests employ cash-market series, although most retail losses occur in high-turnover, high-cost options [39], [40].

G5. Sources of information are considered independently. Behavioural work [27], [28] and finfluencer work [17] are not related to the TA literature.

Not all gaps are equal. The first and fourth are most important to RQ2 and RQ3, because without a measure of adoption and an instrument-aware test we cannot establish whether TA or something around it explains the losses. The others form the research agenda in Section 6.

The present review addresses these gaps in four ways. The second gap is filled by partitioning the evidence into rule-level and user-level sets and coding each source on an articulated scale. For the third, it compares the Indian statistics, including the FY26 SEBI research, with worldwide evidence. It tracks for each source whether TA use, instrument and costs were observed. This reveals rather than hides the first and fourth gaps, and it puts the behavioural and information-source research into the same framework, which tackles the fifth. The outcome is a framework and set of propositions in Section 4 that future account-level work can test.

Methods

This section describes the review procedure so that another researcher can follow, check and replicate it. This study is a systematic literature review, an approach that aims to make the selection and synthesis of evidence clear and open to examination [41]. The evidence consists of peer-reviewed studies, regulator datasets and practitioner reports, and as such the study is best defined as an integrative systematic review, a type tailored to synthesising multiple kinds of evidence in a framework rather than pooling effect sizes [42]. The reporting is based on the PRISMA 2020 statement for identification, screening, eligibility and inclusion [43].

The work was conducted in six steps: (1) scoping and structuring of the research objectives, (2) structured searching, (3) screening against pre-specified eligibility requirements, (4) quality appraisal, (5) data extraction and coding and (6) synthesis. The workflow is shown in Figure 1. The searches and screening took place in November 2026.

We opted for a systematic review rather than a traditional narrative review, which allows the reviewer to select sources according to personal taste. A bibliometric study would have shown publication trends but would have offered little about what the sources conclude about profitability. A meta-analysis was not possible, as the studies varied considerably in markets, tools, durations and outcome measures, and few reported comparable effect sizes.

The design is qualitative and interpretive, with descriptive quantification used for support. The goal is to understand the association between the retail boom, TA use and trading outcomes, rather than to estimate a single effect. The study is based on secondary data only. Differences across sources [44] called for a narrative synthesis with tabulation and thematic categorisation. The individual source is the unit of analysis. Each source was considered as a set of claims concerning scale,

behaviour, methods and outcomes and compared with the others.

Before extraction, each of the four study topics was allocated coding categories to prevent the analysis from drifting into interesting but irrelevant subjects. The review is exploratory, and the propositions in Section 4 are derived from the evidence and proposed for later testing rather than as hypotheses tested here. The review problem was formulated in five parts following the PICOC format [45]:

Phenomenon: The rise of retail participation and its application of technical analysis in emerging markets.

Intervention or exposure: Use of TA rules, indicators and related trading tools.

Comparison: Buy-and-hold benchmarks, non-TA users and the established market evidence.

Outcomes: Profitability, incidence of loss, trading frequency, costs and persistence.

Context: India and other emerging markets.

The target population is the corpus of scholarly, regulatory and high-quality practitioner material on retail investing and technical analysis in developing markets, and the developed-market studies needed to comprehend it. Sampling was purposeful and criteria-based [46]. Sources were chosen for their relevance and quality, not by random selection, as the purpose was to capture the most informative sources about the study issues rather than a statistically representative sample. Table 2 shows the eligibility rules.

Table 2. Eligibility requirements

Dimension	Inclusion	Exclusion
Subject	Use, profitability or forecasting capability of technical analysis Retail or individual investor participation, trading behaviour or consequences	Institutional-only studies Fundamental-analysis studies with no connection to trading rules or retail behaviour
Location	Emerging markets, notably India Developed-market studies where they are fundamental or directly analogous	Commodity-only studies Cryptocurrency-only studies
Type of publication	Peer-reviewed journal articles One working paper with complete text Regulator and exchange publications A few identified practitioner reports	Unsigned blogs Broker marketing material Opinion without data
Period	1992 foundational studies; Indian market data to November 2026	Material that could not be dated
Language	English	Other languages
Evidence	Empirical, review or regulator data sources with identifiable technique, sample and date	Sources without method, sample or date

The window opens in 1992 when Brock and colleagues laid the framework for modern rule-based tests [14]. Theoretical works on efficiency, adaptive markets and behavioural finance are used as interpretive anchors and are not included in the corpus [10], [11], [30], [31], [32]. Following the guidance on grey literature in management reviews [47], practitioner and press-reported material was only accepted if the sponsor, sample and date could be established, and was never used to support a claim without a peer-reviewed or regulator counterpart or an explicit label.

The adequacy of the sample was assessed by saturation [48]. The search proceeded until new searches largely returned sources already found or content outside the eligibility restrictions, and until later sources reinforced existing themes without adding new codes. This is a practical criterion for a purposive selection. It does not mean that the corpus is exhaustive, and the limitation is pointed out in Section 6. The choice to draw from four streams, and not only India-specific TA examinations, is intentional. The India-specific TA literature is scarce, and the questions of information, behaviour and outcomes are better answered by integrating it with worldwide retail-trading research and regulator data.

Data collection and tools-

The data are secondary data. Records were identified by structured keyword searches of open web sources, including publisher portals, SSRN and RePEc-type repositories and websites of regulators and exchanges, as well as backward chaining from the reference lists of the most relevant research. The search was conducted using five concept blocks combined with Boolean operators (Table 3). A first pass combined blocks A, B and C. A second pass substituted blocks D and E to obtain evidence on outcomes and information sources.

Table 3. Search blocks and example strings

Block	Terms (title, abstract and keywords)	Goal
A: Engagement	"individual investors" OR "retail investors" OR "investor base" OR "demat accounts"	Captures the boom

Block	Terms (title, abstract and keywords)	Goal
B: Methodology	"technical analysis" OR "technical trading rules" OR "moving average" OR "RSI" OR "chart"	Captures TA
C: Environment	India OR "emerging market*" OR Nifty OR Sensex OR NSE OR Brazil OR Taiwan	Captures context
D: Results	profitab* OR loss* OR "net loss" OR "day trading" OR derivatives OR options	Captures outcomes
E: Influences	finfluenc* OR "social media" OR FOMO OR herding OR "trading apps"	Captures information sources and behaviour

Retrieval strategy: A AND B AND C (first pass); A AND D AND C and A AND E AND C (second pass).

The screening was in three stages. Titles and abstracts were screened against inclusion criteria initially. If the text was readily available, the records were then reviewed in full; otherwise they were judged through the abstract and publishing information. Claims obtained from abstract-only sources were limited to what the abstract stated. Inclusion was then verified through the evaluation in Section 3.6. The final corpus is made up of 27 sources: 19 peer-reviewed papers, one working paper, five regulator or exchange datasets and two practitioner reports.

Several studies conducted by SEBI, particularly for FY25 and FY26, were consulted through the regulator's press summary and through news reporting of the studies, as full reports were not obtained. Figures extracted from them are referred to the document actually consulted and are marked as reported. The historical series have been compiled from the declarations of regulators, exchanges and depositories and cross-checked where possible. For instance, CDSL's reported 18.01 crore accounts as of 31 March 2026 [49] are in line with a total of roughly 22.5 crore when combined with NSDL's 4.51 crore accounts (May 2026) [2], [49].

The extracted information was recorded in a common form (Table 4) to enable all sources to be compared on identical attributes.

Table 4. Data extraction form

Field	Contents
Citation information	Authors, date, source, document type, level
Stream	A. TA use and profitability; B. Retail behaviour and outcomes; C. Regulator and exchange data; D. Social media and finfluencers
Setting	Country or region; instrument (cash, futures, options); period
Design	Rule test; survey; transaction-record study; regulator dataset; content analysis; review
TA content	TA use, rules or indicators measured; type of rule
Result	Direction of result and treatment of costs
Appraisal	Results of the criteria in Section 3.6

Rules were made for borderline cases. A retail trading study that did not include TA was kept as a user-level outcome study but not counted as evidence on TA itself. If the same study was published as a working paper and as a journal article, the journal article was used. Each decision was entered into a spreadsheet with source, stage reached, decision and justification, which also acted as the data-management file.

Analysis was in two stages. The first was descriptive mapping, counting sources by date, stream, design and context to indicate the shape of the evidence. The second was thematic synthesis following the phases of thematic analysis established by Braun and Clarke [50]. Extracted statements were coded first, organised into candidate themes, validated against the entire set of extracts and then named. Coding was largely inductive, but some deductive anchors were drawn from the research questions and from behavioural finance (loss aversion, herding, overconfidence and the disposition effect).

Two simple scales were fixed a prior to give a direction to each study, for comparing rule-level and user-level evidence. For rule tests the codes are: supportive (profitable or predictive, at least before costs, in the main tests), conditional or mixed (profits depend on the rule, period, market phase or costs) or unsupportive (no profit or predictive power). For user-level studies the codes are: net gain, net loss or mixed for the investors studied. No direction was assigned to surveys and reviews of TA use. These codes represent the reviewer's judgements from the sources' own abstracts and findings and are provided in full so that readers may disagree. Inferential statistics were not needed. The tabulation was performed in a

spreadsheet and the figures were created in Python using matplotlib.

A coding path illustrates the thematic construction. Extract: SEBI's FY26 analysis shows that 87.7 per cent of individual traders lost money and that the losses were concentrated in options [9], [39]. Code: "high and persistent loss incidence"; "instrument: options". Candidate theme: the result is driven by the instrument and the frequency. This was eventually combined with the matched-data finding from the Dutch study that TA users did worst when trading options often [35] and created Theme T4. Propositions were then constructed abductively from patterns identified in multiple sources.

Reflexivity was also practised. The reviewer has a background in marketing and behaviour and may be inclined towards behavioural explanations. To reduce this, theme names state what sources report, and findings that cut against the behavioural reading, such as supportive rule tests, are reported in full. Informally, the strength of support for each assertion was assessed: a claim was regarded as better supported if at least two independent sources from separate streams agreed, and as speculative if it relied on a single source or on inference.

Quality appraisal was conducted using five criteria adapted from standard practice in systematic reviews [41], [42]: (1) relevance to at least one research question; (2) clarity of method or data source; (3) credibility of the outlet or issuer, through peer review or regulatory status; (4) recency and currency of the evidence; and (5) contribution to understanding. All peer-reviewed sources met the first three criteria. Sources were then classified into tiers: Tier 1, peer-reviewed studies; Tier 2, regulator and exchange datasets; Tier 3, practitioner and press-reported material, used for context and for figures traceable to a named issuer. Appraisal determined the weight of a source and was not used to remove sources that reached the minimum threshold.

Credibility is supported by several measures. Full eligibility criteria and search blocks are provided. The reason for including each source can be followed through Tables 1 and 5. Triangulation across streams was built in: a claim regarding outcomes was verified against both academic and regulator sources before it was accepted as a theme. Dependability, in the sense used in qualitative research [51], was indicated by the stabilisation of coding categories after the first full run and by re-reading each extract against the final theme names.

The design's main weakness is reliability. One reviewer did the screening and coding, so inter-coder agreement could not be computed. The work would be strengthened by a second independent coder and a report of agreement using Cohen's kappa [52]. Other limitations should be identified. The search was not a comprehensive export from Scopus or Web of Science but used freely accessible web data. There may be publication bias, because studies that identify profitable rules may be more likely to be published. Different studies, and different vintages of SEBI's own analysis, define populations and costs differently, and FY25 figures were revised between studies [8], [9]; cross-study comparisons are therefore approximate. This synthesis represents a snapshot as of November 2026.

The study uses published secondary data and does not involve human subjects, personal data or interviews, so formal ethical approval and informed consent were not required. However, attention was paid to attribution: the original language was paraphrased, numbers reported in the press were attributed to the document consulted, and the reference list was reviewed so that every cited work is included in it and every listed work is cited in the text.

Results

The corpus consists of 27 sources and ranges from 1992 to 2026. Their distribution by time and stream is given in Figure 2. Of the 27, 14 were released in 2020 or later, and all the regulator, exchange and finfluencer sources fall within this era, which indicates how recent the statistics on the surge are. By setting, 14 sources are India-focused or include India, four relate to other emerging markets (two Asian and Latin American TA studies, the Taiwanese data and the Brazilian data) and nine are developed-market or international studies.

The design of the sources is given in Table 5. There are nine rule-level tests and four transaction-record investigations, plus one matched survey-and-trading study. Only three are Indian rule tests and only two are Indian behavioural surveys. None of the corpus directly estimates TA adoption by Indian retail investors.

Table 5. Corpus by stream and design (n = 27)

Stream and design	n	Sources
A. TA use and profitability: rule-level tests	9	Brock et al. [14]; Lo et al. [33]; Neely et al. [34]; Bessembinder & Chan [18]; Ratner & Leal [19]; Gunasekarage & Power [20]; Mitra [21]; Muruganandan [22]; Tadas et al. [23]
A. TA use: surveys and reviews	3	Menkhoff [12]; Menkhoff & Taylor [13]; Park & Irwin [15]
B. Retail outcomes: transaction records	4	Barber & Odean [24]; Barber et al. [25]; Chague et al. [26]; Barber et al. [29]
B. Retail outcomes: matched survey and trade data	1	Hoffmann & Shefrin [35]
B. Behavioural surveys (India)	2	Gupta & Shrivastava [27]; Kumar et al. [28]
C. Regulator and exchange data (India)	5	SEBI FY22–FY24 study [7]; SEBI FY25 study [8]; SEBI FY25–FY26 study [9]; SEBI Investor Survey 2025 [16]; NSE investor statistics [5]

Stream and design	n	Sources
D. Social media and finfluencers (India)	3	CFA Institute [17]; CFA Institute [36]; Henriques et al. [37]

Historical data on the retail boom (RQ1)

Figure 3 shows the growth of demat accounts. The stock rose from about 2.4 crore in October 2015 [1] to 5.5 crore at the end of FY21 and 22.5 crore at the end of FY26 [2]. Annual additions rose from 1.4 crore in FY21 to a peak of 4.1 crore in FY25, then fell to 3.2 crore in FY26, a drop of about 22 per cent [2]. NSDL alone added a record 59.3 lakh accounts in FY26 [49]. The boom is therefore still growing, but at a slower pace.

Account counts overstate the number of people, because one investor can hold several accounts. NSE reported 26.14 crore registered trading accounts but 13.24 crore unique registered investors on 30 June 2026, a ratio of about two to one [3], and the unique-investor count rose from 12 crore in September 2025 [53]. Figure 4(a) shows the two series. The SEBI Investor Survey 2025 adds the household view: 63 per cent of households are aware of a securities product, but only 9.5 per cent participate, with 15 per cent in urban and 6 per cent in rural areas [16] (Figure 4(b)). Table 6 collects the main indicators.

Table 6. Selected indicators of the retail boom

Indicator	Value	Source
Demat accounts	2.4 crore (Oct 2015); 5.5 crore (FY21); 22.5 crore (FY26)	[1]; [2]
NSE unique registered investors	12 crore (Sep 2025); 13.24 crore (30 Jun 2026)	[53]; [3]
NSE registered trading accounts	26.14 crore (30 Jun 2026)	[3]
Households participating	9.5% (32.1 million); urban 15%, rural 6%	[16]
Individuals' share of NSE market capitalisation	18.7% (direct and via mutual funds, Mar 2026)	[5]
Mobile share of cash-market turnover	More than one-fifth (2026)	[5]
Active individual F&O traders	106.2 lakh (FY25); 87.5 lakh (FY26)	[9]
Traders under 30, share of individual F&O traders	43% (FY24 and FY26)	[7]; [39]

Derivatives speculation and trading outcomes (RQ1, RQ3)

SEBI's first analysis indicated that 89 per cent of individual equity F&O traders lost money in FY22 [54]. For FY22 to FY24, 1.13 crore unique individual traders suffered a collective net loss of ₹1.81 lakh crore including transaction costs, and 93 per cent of them lost money [7]. In FY24 alone, 91.1 per cent lost, with an average net loss of ₹1.20 lakh among about 73 lakh loss-makers; traders under 30 made up 43 per cent of participants, up from 31 per cent a year earlier, and about 93 per cent of them lost money; and over three-quarters had declared annual incomes below ₹5 lakh [7]. Losses did not lead to exit: more than three-quarters of loss-makers continued to trade after two successive loss years [55]. On the opposite side of the trades, proprietary traders and foreign portfolio investors made gross gains of roughly ₹33,000 crore and ₹28,000 crore respectively in FY24 [56].

The two later studies show a small improvement in the share of losers but not in the average loss. Aggregate net losses were revised to ₹1.12 lakh crore, with 90.9 per cent losing in FY25 [9]. The loss share declined to 87.7 per cent in FY26 and aggregate net losses to ₹91,685 crore, the first year-on-year decline in aggregate losses between FY22 and FY26 [39]. However, the average net loss per active trader grew 2.4 per cent to ₹1.17 lakh [9]. Retail investors lost ₹3.85 lakh crore between FY22 and FY26, and options contributed 92 per cent of retail losses in FY26 [39]. Figure 5 shows the loss share and aggregate losses.

When regulation tightened, participation went down. Active individual traders declined by 18 per cent, from 106.2 lakh to 87.5 lakh in FY26, and new entrants contracted by around 40 per cent [9], [57]. Costs matter: individual traders paid roughly ₹24,859 crore in transaction charges in FY26, and about 4.4 lakh traders who were profitable before costs ended the year with a net loss [40]. Portfolio size is a good indicator. Of the individual traders in derivatives, almost 35 per cent had no equity holdings at all, approximately 78 per cent had portfolios of less than ₹1 lakh, and loss rates came down from 93 per cent for those with no holdings to 58 per cent for those with more than ₹10 crore [38], [57]. The young did worse: 89 per cent of traders under 30 lost money, compared with 81 per cent of those over 60 [39].

Key findings by theme (RQ2, RQ3, RQ4)

Thematic analysis revealed six themes, summarised in Table 7 and described below.

Table 7. Analysis of themes

Theme	Key insight	Representative sources
T1 Scale and speed	Participation has expanded several-fold since FY21, but remains small and concentrated at the household level	[2]; [3]; [16]
T2 Options concentration	Speculative activity is concentrated in short-dated options among the young and those with tiny portfolios	[7]; [39]; [38]
T3 Use of TA	Professionals use TA and speculators like it, but how many Indian retail investors use it is unknown	[12]; [35]; [17]
T4 Two levels of evidence	Rule-level tests are supportive or conditional; every user-level study indicates net losses	[14]; [21]; [22]; [26]; [9]
T5 Moderators	Outcomes vary with cost, leverage, behavioural bias, finfluencer exposure and portfolio size	[27]; [28]; [36]; [40]
T6 Regulation	Contract-size and expiry constraints reduce participation faster than loss rates	[8]; [9]; [36]

T1: Scale and speed. The entire corpus suggests very strong growth from FY21, with deceleration in FY26 and the 2026 market correction serving as the first cohort test. Headline data should be viewed with care, given the difference between awareness and participation [16] as well as between accounts and unique investors [3]. A reasonable summation is that India added a lot of accounts, a smaller number of investors and a still smaller number of active traders.

T2: Options concentration. The evidence of loss is concentrated in one area. Options accounted for 92 per cent of retail losses in FY26 [39], the traders were young on average [7] and those with modest portfolios were a substantial component of the losses [38]. SEBI itself has remarked that India's index-options trading volume is excessive relative to international standards [6]. So the problem, as it appears in the data, is more of a derivatives problem than a broad equity-investing problem.

T3: Use of TA. TA is used by professionals [12], [13], and in the Dutch retail sample those who used TA were more speculative, more concentrated and lower-earning [35]. The corpus provides only indirect signals for India: CFA Institute identifies finfluencers as an established source of information for Indian retail investors [36], and one-third of the 48 finfluencers it studied provided clear buy, hold or sell advice [36]. This is consistent with the use of TA but does not measure it. Thus, the first gap in Section 2.3 remains open.

T4: Two levels of evidence. The difference between these two kinds of evidence is shown in Figure 6. Five of the nine rule-level tests are supportive and four conditional, and none is unambiguously unsupportive. All eight user-level outcome studies (five from academia and three from SEBI) reveal net losses. The conditional tests provide the clue to the reconciliation. Mitra discovered returns but cautioned about the costs of frequent trading [21]; Muruganandan found results depending on the market phase that did not compensate for risk [22]; and Tadas et al. tested a brief 2022 window on large stocks [23]. In each case the test was undertaken on cash-market series with simple cost assumptions, and none included the options leverage and turnover that account for most retail losses.

T5: Moderators. Four moderators recur. Costs: transaction costs turned profitable traders into losers for hundreds of thousands of accounts in FY26 [40]. Behavioural bias: Indian retail judgements are influenced by herding, loss aversion and overconfidence, and fear of missing out enhances them [27], [28]; the disposition effect and the slowness to realise losses are long-standing results [31], [32]. Attention and information: zero-commission apps and social media channels draw investors into stocks that later disappoint [29], few Indian finfluencers are registered and many investors never check credentials [17], [36]. Experience: Brazilian day traders [26] showed no indication of learning, and Indian statistics show most loss-makers persevere through losses [55].

T6: Regulation of inputs. When contract sizes were increased and weekly expiries restricted, participation declined [8], and the FY26 study indicates a reduced number of active traders, fewer entrants and a lower aggregate loss, but a loss share that fell by just 3.2 percentage points and a larger average loss [9]. On the information side, SEBI's approach is based on whether the content shifts from education to advising, and CFA's follow-up evaluation identified a regulatory gap that still remains [36]. These facts imply that frictions decrease exposure but do not, by themselves, improve the decisions of those who stay.

Framework and propositions

The six themes are integrated in Figure 7. The growth is driven by enablers such as digital onboarding, mobile apps, low-cost brokerage, weekly index options and social media. The surge adds new users to TA, shaping trading behaviour toward more frequent, short-dated, leveraged trades. Outcomes are then less a function of the indicator and more a function of the moderators (costs, behavioural bias, information quality, age and portfolio size). Poor outcomes feed back into regulation, which changes the enablers.

Five propositions are presented in Table 8. They are drawn from patterns across sources and were not tested here.

Table 8. Propositions drawn from the review

No.	Proposition	Core base
P1	TA use is strongest among post-2019 newcomers and under-30 investors who come on board via mobile apps	[5]; [7]; [4]
P2	User-level profitability does not inherit rule-level profitability when short-dated options, leverage and transaction costs are involved	[21]; [22]; [39]; [40]
P3	Behavioural bias (FOMO, herding, overconfidence) increases the trading frequency of TA users and worsens results	[27]; [28]; [35]
P4	Small-portfolio investors' exposure to unregistered finfluencers amplifies TA-based speculation	[17]; [36]; [38]
P5	Regulatory frictions diminish participation more quickly than loss incidence; outcomes improve largely when exposure is moved away from options	[8]; [9]

The amount of support varies by proposition. P2 has the best support, since independent source streams point the same way. P3 and P5 are moderately supported, the latter with only two observation points. P1 and P4 are the most speculative, as TA adoption itself is unmeasured in the corpus.

Relating the findings to the aims

Table 9. Research objectives and findings

Goal	Response	Themes
RO1	The surge is huge and rapid but waning; accounts overestimate investors; activity is concentrated in options among the young and those with tiny portfolios	T1, T2
RO2	TA may plausibly be used by Indian retail investors, although this is unmeasured; evidence is from professionals and a Dutch retail sample	T3
RO3	Rule-level evidence is supportive or conditional; all user-level studies reveal net losses	T4
RO4	Results separated by instrument, bias, information and portfolio size; costs; framework and five propositions proposed	T5, T6; §4.5

Discussion

Interpretation of findings

The conclusion is that the retail-TA question has been asked at the wrong level. A rule that earns a premium on an index can nonetheless lose for a person who trades it through short-dated options with a small portfolio, high turnover and charges of around ₹25,000 crore a year in aggregate [40]. This is how both rule-level and user-level evidence can be correct. It also explains why the loss share has not moved: regulation has decreased exposure, but the incentives facing those left are the same.

Comparison with prior studies

The results are in line with international retail-trading evidence showing that active individuals lose [24], [25], [26] and that TA users in a Dutch sample underperformed, especially when trading options often [35]. The Indian figures are, if anything, starker than the Brazilian ones in terms of the scale of involvement and confirm the absence of learning described by Chague and colleagues. The results differ in emphasis from the older emerging-market TA studies. Those studies explored whether markets were inefficient enough for rules to work [18], [19], [20]. Present evidence implies that even if they are, the retail population is not positioned to profit.

Contribution

The novelty of the study lies in the divide between rule-level and user-level evidence, in the compiled Indian data series through FY26, and in the framework that positions TA among enablers, behaviour, moderators and regulation. It also explicitly states what the corpus cannot reveal, namely that TA adoption among Indian retail investors has not been measured.

Implications

For regulators, the evidence supports measures targeting decisions and information as well as contract size, including clearer risk disclosure at the point of trade and monitoring of finfluencer content. The findings imply that platforms should consider the impact of charts, alerts and default leverage on trading frequency. Educators should teach indicator skills together with costs, position sizing and evidence on persistence. The data suggest that investors should not bet on short-dated options but rather hold larger, diversified portfolios, although the observed portfolio-size pattern does not prove causation [38]. For researchers, the immediate need is account-level data recording method, instrument and costs together.

Conclusions, Limitations and Future Research

This paper has explored the link between the retail boom in India and the use of technical analysis, and the evidence on consequences. Its main finding is that the evidence at the rule level on TA is mostly supportive or conditional, whereas every study at the user level in the corpus reports net losses. The difference is explained by the way in which TA is used: through what instrument, at what frequency, at what cost, under what behavioural pressures and from what sources of information. The boom in India has risen from roughly 5.5 crore demat accounts in FY21 to 22.5 crore in FY26. However, 87.7 to 91.1 per cent of individual derivatives traders lost money in each of the last three years reviewed by SEBI [7], [8], [9].

Two caveats should be mentioned. First, the corpus is limited (27 sources), was generated from freely accessible web sources and not from a full Scopus or Web of Science export, and depends on newspaper summaries for some SEBI results, so relevant work may have been overlooked and some figures depend on reporting. One reviewer did the screening and coding, therefore inter-coder reliability is not reported. Second, the area is fast-moving and the synthesis is as of November 2026; SEBI statistics for prior years have been revised between studies.

Future research can progress in four directions. First, research should quantify TA adoption among Indian retail investors directly, for example by comparing platform data on charting activity with account outcomes. Second, rule tests should be performed using post-2020 data with realistic costs, including options. Third, quasi-experimental work could examine whether the 2024–2025 regulatory measures altered behaviour or only participation. Fourth, comparative studies across emerging markets such as Brazil, Taiwan and Indonesia could indicate whether the patterns in P2 and P5 hold outside India.

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