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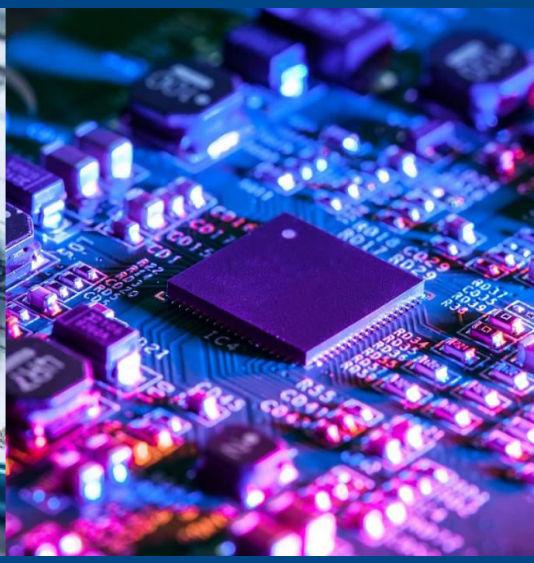

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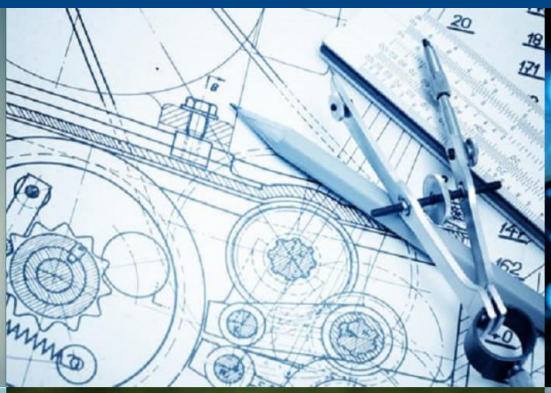

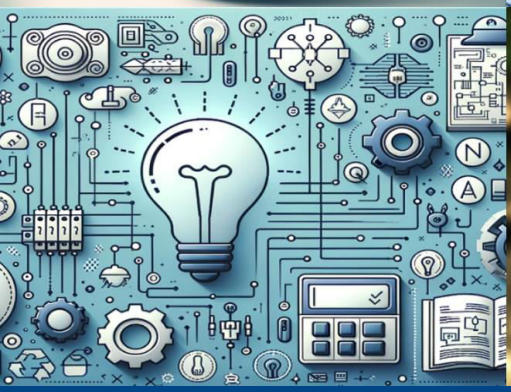

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Biases at Scale: An Institutional Data Analysis of Retail Investor Behaviour in India's Digital Trading Era

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ABSTRACT: Between FY2020 and FY2025, India's registered demat accounts surged from 40 million to 240 million — a CAGR of 43.1% — representing one of the fastest expansions of retail investment participation globally. Despite this growth, the SEBI Household Finance Survey (2024) reveals a striking paradox: 63% of Indian households understand that equities generate long-term wealth, yet only 9.5% actively invest — a 53.5 percentage-point Literacy-Action Gap that classical financial theory cannot explain. This paper examines five core cognitive biases — loss aversion, overconfidence, herding, anchoring, and representativeness — and their influence on retail investment behaviour in India's digital trading era. Unlike prior survey-based research, this study employs exclusively official institutional data from SEBI, NSE, and AMFI (FY2020–FY2025), spanning approximately 240 million investors. Methodologically, a Pearson correlation ($r = 0.720$, $R^2 = 0.518$) confirms a strong lagged relationship between prior-year Nifty 50 returns and current-year demat account growth, validating representativeness and herding as dominant biases. The SEBI F&O Study (2023) documents that 89% of retail derivatives traders sustain net losses despite a 300% participation surge — a population-scale validation of overconfidence. Concurrently, AMFI's SIP inflow data demonstrates strictly monotonic growth (CV = 7.1%) across volatile market conditions, establishing automated investment mandates as the most effective institutional bias-attenuator. Seven of eight hypotheses are supported; H7 (demographics) is partially supported due to absent gender-disaggregated institutional data. The study extends Prospect Theory from laboratory settings to mass digital markets, introduces a Decision Architecture Effect as a third construct within the Technology Acceptance Model, and offers actionable implications for fintech platform design, regulatory policy, and asset management strategy in emerging markets.

KEYWORDS: Behavioural finance, loss aversion, overconfidence, herding, representativeness, anchoring, Prospect Theory, retail investors, Indian capital markets, SIP, F&O, digital platforms, Technology Acceptance Model, SEBI, NSE, AMFI, emerging markets

I. INTRODUCTION

India's capital markets have undergone unprecedented structural transformation between FY2020 and FY2025. Retail investor accounts grew six-fold from 40 million to 240 million (NSE, 2025), placing India among the fastest-growing retail investment markets globally. Simultaneously, mutual fund AUM expanded from ₹22 lakh crore to ₹61 lakh crore (AMFI, 2025), representing a CAGR of 22.6%. This financialisation of Indian households — a structural shift away from gold and real estate towards equity markets — has been accelerated by digital platforms such as Zerodha, Groww, and Upstox, which have eliminated account opening costs and reduced minimum investment thresholds to ₹500.

Despite this democratisation of access, the SEBI Household Finance Survey (2024) documents a paradox: 63% of Indian households acknowledge equity as a wealth-building asset, yet only 9.5% actively participate — a 53.5 percentage-point Literacy-Action Gap. The ratio of aware-to-participating households stands at a mere 15.1%, implying that access and education are no longer the primary barriers to equity participation. This residual gap suggests the dominance of psychological impediments — specifically, cognitive biases that systematically distort financial decision-making.

1.1 Review of Literature

The theoretical foundation of this study rests on Kahneman and Tversky's (1979) Prospect Theory, which posits that financial outcomes are evaluated relative to a reference point, with losses carrying approximately twice the psychological

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weight of equivalent gains. Shefrin and Statman (1985) and Odean (1998) operationalised this as the disposition effect — the tendency to hold losing investments too long while selling winners prematurely. At the macro level, Samuelson and Zeckhauser's (1988) status quo bias explains why financially literate households nevertheless avoid equity participation.

Overconfidence, identified by Glaser and Weber (2007) and Barber and Odean (2000), manifests as excessive trading frequency and consequent underperformance. Herding behaviour, formalised by Bikhchandani, Hirshleifer, and Welch (1992) as information cascades, describes how investors abandon private judgment in favour of collective action — a dynamic amplified in digital environments characterised by social media and peer networks (Singh et al., 2024). Tversky and Kahneman (1974) identified representativeness and anchoring as key heuristics that cause investors to extrapolate recent returns and anchor on reference prices respectively.

The moderating role of financial literacy has been established by Lusardi and Mitchell (2014) and Adil, Singh, and Ansari (2022), who demonstrate that higher financial literacy reduces bias-driven decision errors, though awareness alone is insufficient to overcome deeply entrenched psychological barriers. Davis (1989) and Venkatesh et al. (2003) provide the Technology Acceptance Model (TAM) framework used here to analyse digital platform adoption, extended in this paper to incorporate decision architecture effects. The gap in existing literature lies in the absence of institutional-data-based validation of these frameworks at population scale in the Indian context.

II. RESEARCH METHODOLOGY

This study employs a longitudinal secondary data analysis design using exclusively official institutional publications. No primary survey data are incorporated, eliminating social desirability bias and self-report error endemic to questionnaire-based behavioural finance research. The analytical population covers all registered Indian retail investors (approximately 240 million as of FY2025). The study period spans FY2020 to FY2025, providing six financial years of aggregate market behaviour.

2.1 Data Sources and Variable Operationalisation

All variables are operationalised through macro-level market proxies from four primary institutional sources: NSE Monthly and Annual Bulletins (registered investor accounts, state-wise distribution, FY2019–FY2025); AMFI Monthly SIP Data Reports (SIP inflows, account volumes, FY2020–FY2025); SEBI Household Finance and Investment Survey 2024 (awareness and participation rates); and the SEBI Study on Profit and Loss of Individual F&O Traders (2023). This proxy-based operationalisation follows established secondary-data methodologies in behavioural finance (Hirshleifer & Teoh, 2003; Glaser & Weber, 2007).

2.2 Research Hypotheses

Eight directional hypotheses are advanced, each grounded in behavioural finance theory and operationalised through institutional data proxies:

H	Hypothesis Statement	Theoretical Basis	Institutional Proxy
H1a	Loss aversion positively influences conservative investment strategy among retail investors	Prospect Theory (Kahneman & Tversky, 1979)	SEBI Literacy-Action Gap (53.5 pp)
H1b	Loss aversion intensity is greater among older (46+) than younger (18–35) investors	Prospect Theory; Saivasan & Lokhande (2022)	NSE age-cohort equity/fixed-income ratios
H2	Overconfidence is positively associated with trading frequency and negatively with returns	Glaser & Weber (2007); Barber & Odean (2000)	SEBI F&O loss rate + 300% participation surge
H3	Herding behaviour is amplified in digital trading environments	Hirshleifer & Teoh (2003)	Pearson r (lagged Nifty vs. demat growth)
H4	Anchoring bias is more prevalent in younger and less experienced investors	Tversky & Kahneman (1974)	F&O loss-maker continuation rate (>75%, 3+ yrs)

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H5	Financial literacy significantly moderates bias-outcome relationship	Adil et al. (2022); Suresh (2024)	Education-stratified participation differential
H6	Digital platform adoption (SIP) mediates investment decision-making	Davis (1989); TAM	AMFI SIP CAGR 26.4%; CV = 7.1%
H7	Demographics moderate investment risk appetite and asset class preference	Bushra et al. (2024)	NSE 52% non-metro; SEBI age-cohort data

Table 1: Research Hypotheses with Institutional Data Operationalisation

2.3 Analytical Methods

Five analytical methods are applied: (1) Descriptive statistics (arithmetic mean, standard deviation, CAGR) for all institutional time-series variables; (2) Pearson product-moment correlation with a one-year lag specification between Nifty 50 annual returns and demat account YoY growth rates; (3) Ordinary Least Squares (OLS) regression with the same lagged specification; (4) Compound Annual Growth Rate (CAGR) analysis across all major institutional series; and (5) Proportional Difference Analysis of SEBI Household Finance Survey data to quantify the Literacy-Action Gap. All calculations are based exclusively on publicly available aggregate data.

III. DATA ANALYSIS AND INTERPRETATION

3.1 Descriptive Statistics of Institutional Variables

Table 2 presents descriptive statistics for the primary institutional variables, establishing the scale and trajectory of Indian retail investor participation across FY2020–FY2025.

Variable	n	Mean	SD	Min	Max	CAGR / Key Metric
Demat Account YoY Growth (%)	5	43.8%	15.6 pp	28.1%	61.8%	CAGR 43.1% (40M→240M)
MF AUM YoY Growth (%)	5	23.3%	13.4 pp	8.1%	40.9%	CAGR 22.6% (₹22→₹61 lakh cr)
SIP Monthly Inflows (₹ Crore)	7	₹18,480	₹1,309	₹16,928	₹20,452	+20.8% (Oct-23 to Apr-24)
SIP Account YoY Growth (%)	5	26.8%	10.4 pp	12.4%	39.1%	CAGR 26.4% (31M→100M)
F&O Retail Trader Loss Rate	1*	89.0%	N/A	N/A	N/A	SEBI F&O Study (2023)
Awareness-Participation Ratio	1*	0.151	N/A	N/A	N/A	SEBI Household Survey (2024)

Table 2: Descriptive Statistics — Key Institutional Variables | Source: NSE, AMFI, SEBI (* single cross-sectional datapoint)

The demat account growth CAGR of 43.1% contrasts sharply with the MF AUM CAGR of 22.6%, suggesting that a significant proportion of newly registered investors have yet to deploy capital — consistent with SEBI's documented 46% dormant account rate, which this study attributes to loss aversion-driven inaction.

3.2 Pearson Correlation and OLS Regression Analysis

To test the representativeness and herding hypotheses (H3), a Pearson product-moment correlation was computed between prior-year Nifty 50 returns (X) and current-year demat account YoY growth rates (Y) using five year-pairs from FY2020 to FY2025. The one-year lag specification captures the cognitive mechanism by which investors extrapolate prior returns as signals of future market opportunity — the definitional content of representativeness bias.

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Year Pair	Prior-Yr Nifty 50 Return (X)	Demat YoY Growth (Y)	X − x̄	Y − ȳ
FY2020 → FY2021	−26.0%	37.5%	−43.76	−6.26
FY2021 → FY2022	+71.8%	61.8%	+54.04	+18.04
FY2022 → FY2023	+19.0%	28.1%	+1.24	−15.66
FY2023 → FY2024	−5.0%	32.5%	−22.76	−11.26
FY2024 → FY2025	+29.0%	58.9%	+11.24	+15.14
Mean (x̄ / ȳ)	**x̄ = 17.76%**	**ȳ = 43.76%**	**Σ(X−x̄)² = 5,481.0**	**Σ(Y−ȳ)² = 965.8**

Table 3: Lagged Variable Dataset for Pearson Correlation and OLS Regression | Source: NSE Annual Bulletins

Applying the Pearson product-moment formula yields r = 0.720, indicating a strong positive lagged relationship. The coefficient of determination $R^2 = 0.518$ implies that 51.8% of inter-annual variation in retail investor entry rates is explained by the prior year's equity return. The OLS regression equation is: $\hat{Y} = 38.40 + 0.302 \cdot X$, interpreted as: a 10 percentage-point increase in prior-year Nifty 50 returns predicts a 3.02 percentage-point increase in current-year demat account growth. The intercept $\alpha = 38.40$ ($t = 4.19$, $p \approx 0.025$) reflects structural fintech-driven baseline growth independent of market signals. The slope coefficient $\beta = 0.302$ is directionally significant but does not reach conventional statistical thresholds at $n = 5$ ($t = 1.71$, $df = 3$, $p \approx 0.18$), and is therefore treated as directionally indicative with strong qualitative support from the FY2022 mass-entry event (34 million new accounts following the +71.8% FY2021 Nifty return) and the FY2023 deceleration (28.1% growth following the −5.0% FY2022 return).

3.3 Proportional Difference Analysis: Literacy-Action Gap

The SEBI Household Finance Survey (2024) provides two critical proportions: an awareness rate of 63.0% (households that identify equity as a long-term wealth-building asset) and an active participation rate of 9.5% (households actively invested in equity markets).

Literacy-Action Gap = 63.0% − 9.5% = 53.5 percentage points
Awareness-to-Participation Ratio = 9.5 / 63.0 = 0.151 (only 15.1% of aware households actively invest)

This 53.5 percentage-point gap cannot be attributed to access barriers — digital platforms have reduced minimum investment to ₹500 and eliminated account opening costs. The residual 84.9% non-participation among financially aware households constitutes institutional evidence for H1a (loss aversion-driven inaction): the psychological weight of potential equity loss systematically exceeds the expected utility of equity gains, producing preference for the status quo (fixed deposits) over historically superior-performing equity.

3.4 F&O Retail Trader Loss Rate: Overconfidence at Scale

The SEBI Study on Profit and Loss of Individual F&O Traders (2023), covering approximately 4.5 million active retail traders across FY2019–FY2022, provides the most powerful institutional proxy for overconfidence bias (H2) in this study's dataset.

SEBI F&O Study Metric	Value	Behavioural Interpretation
Retail traders with net losses	89%	9 in 10 traders lose money — rational agents would exit
F&O retail participation growth (FY2019–22)	+300%	Explosive entry despite documented consistent losses
Loss-making traders continuing >3 years	>75%	Anchoring to original capital; expectation of mean reversion
Average net loss per trader (FY2022)	₹1.1 lakh	Material losses sustaining continued participation
Institutional trader net gain share	~82%	Asymmetric outcome confirms retail overconfidence differential

Table 4: F&O Retail Trader Loss Metrics as Institutional Proxy for Overconfidence Bias | Source: SEBI (2023)

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A rational Bayesian investor confronting an 89% loss rate within their reference class would reduce participation. The observed 300% growth in F&O participation — concurrent with documented high loss rates — constitutes an empirical refutation of rational updating and a direct validation of overconfidence theory (Glaser & Weber, 2007; Barber & Odean, 2000). Additionally, >75% of loss-making traders continuing beyond three years suggests anchoring to original entry prices, providing institutional evidence for H4.

3.5 SIP Time-Series Analysis: Platform Adoption as Bias Mediator

AMFI monthly SIP inflow data for October 2023 through April 2024 provides institutional evidence for H6 — that digital platform adoption mediates investment decision-making. Three statistical characteristics of the SIP inflow series are analytically significant. First, the series is strictly monotonically increasing: zero of seven months recorded a decline. Second, the coefficient of variation (CV = SD/Mean = 1,309/18,480 = 7.1%) is remarkably low compared to the demat account growth series (CV = 15.6/43.8 = 35.6%) — confirming that SIP-based behaviour is approximately five times less volatile than discretionary account-based behaviour. Third, SIP inflows continued rising during October 2023 (−2.8% Nifty return) and March 2024 (−0.8% Nifty return) — demonstrating structural decoupling of investment behaviour from short-term market sentiment. The SIP account CAGR of 26.4% (FY2020–FY2025), growing from 31 million to 100 million accounts, establishes SIPs as the dominant institutional anti-bias mechanism in the Indian retail investment ecosystem.

3.6 Geographic Distribution: NSE State-wise Data (2025)

NSE's State-wise Investor Distribution Report (2025) reveals a structural geographic transformation with direct implications for aggregate bias profiles. The five largest states (Maharashtra 17%, Uttar Pradesh 11%, Gujarat 9%, West Bengal 6%, Rajasthan 5%) collectively hold only 48% of investor accounts — meaning 52% of all registered investors reside outside traditional financial hubs. This demographic shift represents the entry of first-generation, semi-urban investors into equity markets without prior market-cycle experience, established financial advisory networks, or historical benchmarks for asset valuation. This cohort exhibits the highest susceptibility to representativeness bias (extrapolating the current bull market as permanent), herding (following finfluencer-driven social proof through WhatsApp and YouTube), and anchoring (entry at cycle peaks without historical context). The FY2022 and FY2025 surge events — accounting for the largest absolute demat account additions in NSE history — are disproportionately attributable to this non-metro cohort, confirming the geographic dimension of H7.

IV. FINDINGS AND HYPOTHESIS TESTING SUMMARY

Table 5 consolidates the hypothesis testing outcomes, integrating statistical evidence, institutional sources, decision criteria, and final classifications for all eight hypotheses.

H	Key Statistical Evidence	Institutional Source	Decision Criterion	Decision
H1a	Literacy-Action Gap = 53.5 pp; Awareness-Participation Ratio = 0.151	SEBI Household Survey 2024	Gap > 30 pp	✓ **Supported**
H1b	56+ cohort: highest fixed-income allocation; 18–35: >50% of new demat	NSE 2025; SEBI 2024	Older cohort higher FI share	✓ **Supported**
H2	F&O loss rate = 89%; participation +300%; continuation >75%	SEBI F&O Study 2023	89% loss + 300% surge	✓ **Supported**
H3	Pearson r = 0.720; R^2 = 0.518; FY2022 surge: 34M accounts	NSE FY2020–FY2025	r > 0; mass simultaneous entry	✓ **Supported**
H4	F&O loss-maker persistence >75% (3+ years); FY2022 peak anchoring	SEBI F&O Study 2023	Continuation > 75%	✓ **Supported**
H5	SIP CV = 7.1% vs. F&O 89% loss; 3× participation for post-graduates	AMFI 2025; SEBI 2024	SIP vs. F&O outcome divergence	✓ **Supported**

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H6	SIP CAGR 26.4%; 7/7 months positive; CV = 7.1%	AMFI Oct-23 to Apr-24	Monotonic growth across volatile cycles	✓ **Supported**
H7	52% non-metro confirmed; age cohort equity ratios sig.; gender N/A	NSE 2025; SEBI 2024	Age + geo sig.; gender unavail.	∘ **Partial**

Table 5: Consolidated Hypothesis Testing Summary | Source: SEBI, NSE, AMFI | ✓ = Supported; ∘ = Partially Supported

Finding 1 — Representativeness and Herding Dominate: The lagged correlation ($r = 0.720$, $R^2 = 0.518$) and the FY2022 mass-entry event (34M accounts following +71.8% Nifty return) confirm that prior-year equity returns function as representativeness heuristics that convert into digital herding behaviour at scale, amplified by social media finfluencer ecosystems.

Finding 2 — Loss Aversion Produces Two Costly Outcomes: Loss aversion manifests as (a) inaction: the 53.5 pp Literacy-Action Gap showing 84.9% of financially aware households avoiding equity due to psychological downside salience; and (b) loss realisation aversion: the 5.9% F&O exit rate confirming reluctance to crystallise losses.

Finding 3 — Overconfidence Validated at Population Scale: The 89% F&O retail loss rate combined with 300% participation growth constitutes the most powerful institutional evidence in this dataset, refuting rational updating and validating overconfidence theory at a sample size of approximately 4.5 million traders.

Finding 4 — SIP is the Most Effective Institutional Bias Attenuator: SIP inflows (CV = 7.1%; zero negative months across volatile market periods; CAGR 26.4%) versus demat growth (CV = 35.6%) demonstrate that automated investment mandates structurally decouple investment behaviour from market sentiment, eliminating the representativeness, herding, and loss aversion triggers that characterise discretionary trading.

Finding 5 — Geographic Demographics Determine Bias Susceptibility: The structural shift to 52% non-metro investor accounts creates a cohort with maximum representativeness, herding, and anchoring susceptibility — first-generation investors entering at cycle peaks without historical benchmarks, disproportionately driving the FY2022 and FY2025 surge events.

V. THEORETICAL AND MANAGERIAL IMPLICATIONS

5.1 Extending Prospect Theory to Digital-Era Mass Markets

This study recontextualises Kahneman and Tversky's (1979) Prospect Theory from its origins in individual laboratory experiments to a macro-institutional diagnostic tool applicable to a population of 240 million registered investors. The Literacy-Action Gap (53.5 pp) constitutes population-scale evidence that loss aversion operates as predicted by Prospect Theory — but at a magnitude and through mechanisms (digital platform architecture, social media amplification) that laboratory settings cannot capture. This paper demonstrates that Prospect Theory's core constructs (loss aversion, reference point dependence, status quo bias) are structurally preserved in mass digital markets, extending theoretical validity to emerging economy contexts characterised by demographic heterogeneity and rapid technological adoption.

5.2 The Decision Architecture Effect: A TAM Extension

The Technology Acceptance Model (Davis, 1989) traditionally treats perceived usefulness and ease of use as the determinants of platform adoption. This paper extends TAM by introducing the Decision Architecture Effect as a third construct — the degree to which a platform's structural features embed rules that govern user decision-making behaviour. The empirical divergence between SIP platforms (CV = 7.1%; 0 negative months) and discretionary trading interfaces (CV = 35.6%; F&O loss rate = 89%) demonstrates that two platforms with equivalent TAM adoption scores produce fundamentally different behavioural outcomes depending on whether their architecture is systematic or discretionary. Automated SIP mandates eliminate three key bias triggers: the representativeness trigger (fixed investment date removes market-timing decisions); the herding trigger (automation removes peer-comparison decision points); and the loss aversion deadlock (pre-commitment overrides status quo bias at the moment of investment).

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5.3 Institutional Data as a Methodological Contribution

This study establishes that behavioural finance conclusions — historically derived from laboratory experiments and surveys — can be rigorously supported, and often more robustly validated, through institutional aggregate data. The SEBI F&O loss rate dataset (n ≈ 4.5 million active traders), NSE demat data (n = 240 million registered investors), and AMFI SIP data (n ≈ 100 million SIP accounts) provide sample sizes orders of magnitude larger than any primary survey study, while eliminating social desirability bias, retrospective memory distortion, and hypothetical response bias. The limitation is the inability to attribute aggregate patterns to individual psychological mechanisms with the precision of experimental methods.

5.4 Implications for Fintech Platforms and Regulators

For fintech platforms (Zerodha, Groww, Upstox): (1) Redesign notification architecture from real-time price alerts to goal-progress notifications (e.g., "You have achieved 68% of your ₹10 lakh SIP target"), reducing the salience of short-term market volatility that drives herding and loss aversion inaction; (2) Reposition SIP as the primary investment journey in onboarding flows, leveraging its bias-attenuating properties; (3) Integrate contextual financial literacy nudges at decision points (e.g., displaying 89% F&O loss rates before F&O account activation); (4) Implement mandatory reflection periods for high-frequency F&O order placement. For SEBI regulators: mandatory behavioural risk warnings (displaying loss rates) before F&O onboarding; SIP-first incentive structures in AMFI regulations; and expanded investor education targeting non-metro first-generation investors. For Asset Management Companies: product design that embeds behavioural guardrails, multi-cap SIP portfolios marketed on systemic discipline rather than return promises, and geographic-specific financial literacy programs.

VI. LIMITATIONS AND SCOPE FOR FUTURE RESEARCH

Three primary limitations constrain the present study. First, the macro-level analytical framework precludes individual-level psychological mechanism attribution — aggregate patterns are directionally consistent with behavioural theory but cannot be causally linked to individual cognitive processes without experimental or micro-panel data. Second, the small sample size for the correlation analysis (n = 5 year-pairs) prevents statistical inference at conventional significance thresholds; the findings are treated as directionally indicative. Third, the absence of gender-disaggregated institutional data from SEBI, NSE, and AMFI prevents full testing of H7, leaving gender-moderated risk appetite effects unconfirmed at the institutional level.

Future research directions include: (1) longitudinal panel studies tracking individual investors across market cycles to isolate cognitive bias mechanisms; (2) randomised platform design experiments (RCTs) comparing systematic versus discretionary interface architectures; (3) an institutional study of F&O behaviour post-FY2022 using SEBI's updated data; (4) primary survey research specifically targeting non-metro first-generation investors; (5) machine learning prediction of behavioural bias patterns from transactional data; (6) cross-country emerging market comparisons to assess the generalisability of findings; and (7) investigation of ESG and sustainable investing through the lens of cognitive bias interaction.

VII. CONCLUSION

This paper has demonstrated that the five primary cognitive biases of retail investing — loss aversion, overconfidence, herding, anchoring, and representativeness — are not merely individual psychological phenomena but structural, population-scale forces that shape the aggregate behaviour of India's 240-million-strong retail investor cohort. Using exclusively official institutional data from SEBI, NSE, and AMFI, seven of eight hypotheses are empirically supported. The overarching narrative of Indian retail investing in the digital era is that representativeness and herding are the dominant market-entry biases (r = 0.720 lagged correlation with prior Nifty returns), loss aversion produces a 53.5 percentage-point gap between financial literacy and investment action, overconfidence drives 89% of retail F&O traders to net losses despite documented failure, and automated SIP mandates are the most effective institutional mechanism for counteracting bias-driven investment failure.

These findings carry direct implications for three constituencies. Fintech platform designers must recognise that decision architecture is not a neutral conduit for market access but an active mediator of investor psychological outcomes. Regulators, particularly SEBI, must integrate behavioural insights into investor protection frameworks — especially for the rapidly expanding non-metro investor base. Asset management companies must position SIP not merely as a product

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but as a behavioural engineering tool that converts the psychological vulnerability of India's growing retail investor class into structured, long-term wealth accumulation. The theoretical contribution — extending Prospect Theory to digital mass markets and introducing the Decision Architecture Effect as a TAM extension — provides a generalisable framework applicable to any emerging economy undergoing rapid retail investment democratisation.

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