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Overconfidence, Herd Behavior and Confirmation Bias among Retail Mutual Fund Investors: A Behavioral Finance Perspective

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ABSTRACT

This study investigates the prevalence and investment consequences of three prominent behavioral biases — overconfidence, herd behavior, and confirmation bias — among retail mutual fund investors in Uttar Pradesh and Uttarakhand. It further examines how these biases vary across gender and investment experience groups, and assesses their collective explanatory power in predicting suboptimal investment decisions. Primary data were gathered from 374 retail mutual fund investors across fourteen cities in UP and Uttarakhand between June and September 2025, using stratified random sampling and a structured questionnaire. Validated Likert-scale instruments measured overconfidence (6 items, Cronbach's α = 0.78), herd behavior (6 items, α = 0.81), and confirmation bias (5 items, α = 0.76). Suboptimal Investment Decisions (SID) were captured through a 5-item scale (α = 0.79). Independent samples t-tests, one-way ANOVA, Pearson correlation, and multiple linear regression were applied for analysis using IBM SPSS 26.0. **Findings:** Herd behavior is the most prevalent bias (52.7% of investors classified as high-herd), followed by overconfidence (46.8%) and confirmation bias (41.2%). Male investors exhibit significantly higher overconfidence than females ($t = 5.69$, $p < 0.001$), while females display greater herd behavior ($t = -2.84$, $p = 0.005$). All three biases decrease significantly with investment experience (ANOVA $p < 0.001$ for each). Herd behavior is the strongest predictor of suboptimal decisions ($\beta = 0.374$, $p < 0.001$), followed by overconfidence ($\beta = 0.318$) and confirmation bias ($\beta = 0.221$). The combined model explains 52.4% of variance in SID (Adjusted $R^2 = 0.516$). During a tracked market correction period, 58.4% of high-herd investors redeemed SIPs versus 19.7% of low-herd investors. This is among the first studies to jointly measure all three cognitive biases through validated instruments and link them empirically to observed investment behaviors — including SIP redemption during corrections — among retail investors in UP and Uttarakhand. The inclusion of social media and WhatsApp group effects as measurable triggers of herd behavior adds contemporary relevance to the behavioral finance literature for this geography.

Introduction

The classical model of financial economics rests on the proposition that investors are rational agents who process available information efficiently, evaluate risk and return systematically, and make investment decisions that maximize expected utility. Mutual fund markets, in this framework, are populated by forward-looking participants whose aggregate behavior produces prices consistent with fundamental value. Decades of empirical evidence, however, have accumulated to challenge this foundational assumption. Investors — retail investors in particular — exhibit recurring, systematic departures from rational decision-making that cannot be attributed to information constraints alone. These departures, collectively studied under the discipline of behavioral finance, reflect the operation of cognitive heuristics, emotional responses, and social influences that distort the investment decision process.

Three behavioral biases occupy a central position in this literature: overconfidence, herd behavior, and confirmation bias. Overconfident investors systematically overestimate their knowledge, forecasting ability, and precision of private signals, leading to excessive trading, under-diversification, and excessive risk-taking. Herd behavior describes the tendency of investors to imitate the decisions of a majority — purchasing what others are buying and redeeming what others are selling — independently of their own private information or analysis. Confirmation bias leads investors to selectively seek, interpret, and recall information that corroborates existing beliefs while discounting contradictory evidence, resulting in excessive concentration in familiar or previously successful funds and resistance to portfolio rebalancing.

In the Indian mutual fund context, these biases have direct and measurable welfare consequences. Overconfident investors trade too frequently, incurring exit loads and taxation on short-term capital gains. Herd behavior amplifies market volatility and produces fund inflows at market peaks and redemptions at troughs — precisely inverting the optimal investment timing suggested by rupee-cost averaging. Confirmation bias sustains investment in chronically underperforming funds because investors selectively attend to positive news about those funds while ignoring comparative performance data.

Uttar Pradesh and Uttarakhand present a particularly valuable context for studying these biases. Both states are characterized by a growing but relatively inexperienced retail investor base, significant social influence networks (community-based information diffusion through WhatsApp groups, neighbourhood investment circles, and religious gathering discussions), and moderate average financial literacy — conditions that prior theory suggests are especially conducive to behavioral bias manifestation. The rapid proliferation of social media financial content since 2020 has added a digital amplification layer to traditionally offline herd information cascades.

Despite this contextual richness, no published study has jointly measured all three biases through validated instruments and linked their measured prevalence to observable investment behavioral outcomes — specifically SIP continuation or discontinuation during market corrections — among retail investors in these states. This study fills that gap through a primary survey of 374 investors, offering the first region-specific behavioral finance evidence for UP and Uttarakhand.

Objectives of the Study

The study pursues the following objectives:

- To measure the prevalence of overconfidence, herd behavior, and confirmation bias among retail mutual fund investors in Uttar Pradesh and Uttarakhand.
- To examine how these three biases differ across gender and investment experience groups.
- To assess the association between each bias and suboptimal investment decisions, including SIP redemption during market corrections.
- To identify the primary social and digital triggers of herd behavior in this investor population.

- To determine the relative predictive strength of overconfidence, herd behavior, and confirmation bias in explaining suboptimal mutual fund investment decisions through multiple regression.

Research Hypotheses

H01: There is no significant difference in overconfidence levels between male and female retail mutual fund investors.

H02: Investment experience does not significantly influence the level of herd behavior among retail investors.

H03: There is no significant association between herd behavior intensity and SIP redemption during market downturns.

H04: Overconfidence, herd behavior, and confirmation bias do not significantly predict suboptimal investment decisions after controlling for investment experience and financial literacy.

Review of Literature

Overconfidence in Investment Decision-Making

Barber and Odean (2001) produced the landmark empirical demonstration of overconfidence in retail investor behavior, using a dataset of 35,000 US household brokerage accounts and documenting that investors who traded most actively earned net annual returns 6.5 percentage points lower than passive holders. Their central argument, grounded in psychological research by Odean (1998), was that overconfident investors overestimate the precision of their private information signals, leading to excessive trading that benefits brokers but harms investor wealth. In their celebrated follow-up study specifically examining gender, Barber and Odean (2001) found that men trade 45% more than women and suffer proportionally greater performance penalties — an early empirical support for male-overconfidence hypothesis in financial contexts.

Pompian (2012) provided an accessible taxonomy of overconfidence sub-biases in the practitioner literature, distinguishing between prediction overconfidence (overestimating forecast accuracy), certainty overconfidence (treating uncertain outcomes as known), and competence overconfidence (overrating personal investment ability). Each sub-form generates distinct behavioral predictions: prediction overconfidence leads to concentrated bets; certainty overconfidence produces insufficient portfolio diversification; competence overconfidence sustains market timing attempts despite documented poor timing outcomes. In the Indian context, Daniel and Titman (2006) noted that overconfidence-driven momentum trading in retail accounts may produce short-term market anomalies that sophisticated institutional investors exploit.

Indian evidence on overconfidence in mutual fund investors is sparse but directionally consistent with global findings. Chandra and Kumar (2012) surveyed 296 retail equity investors in Delhi-NCR and found overconfidence scores significantly correlated with trading frequency and inversely correlated with portfolio Sharpe ratios. Raut and Das (2015) confirmed higher overconfidence among self-employed and business class investors compared to salaried employees — a finding directly relevant to the present study's occupational composition.

Herd Behavior in Mutual Fund Markets

Bikhchandani and Sharma (2001) provided the canonical theoretical treatment of herd behavior in financial markets, distinguishing intentional herding (rational investors follow others due to information asymmetry) from spurious herding (investors share common signals). Their model demonstrated that even a small number of early movers can trigger information cascades where subsequent investors rationally discard their own private information in favor of the apparent consensus — producing fragile market equilibria that are vulnerable to sudden reversal when the cascade assumptions are questioned.

In mutual fund contexts, herd behavior manifests most visibly in fund flow patterns: investor money pours into recently outperforming categories (equity funds following a bull run) and out of recently underperforming ones (debt funds during credit events), amplifying the performance-flow relationship documented extensively in the academic literature. Sias (2004) examined institutional herding in US equity markets and found significant herding coefficients, particularly in small-cap stocks with greater information asymmetry — a parallel to small-city retail investor behavior in Indian markets where information is unevenly distributed.

The role of social media and digital communities in amplifying herd behavior represents a recent and under-studied extension of the traditional herding literature. Han, Tang and Yang (2022) documented that social media stock recommendations in Chinese retail investor communities predicted significant positive momentum in the following two trading sessions, followed by sharp reversals — consistent with a herd-driven overreaction cycle. In India, the proliferation of WhatsApp investment groups, Telegram channels, and YouTube financial influencers since 2019 has created new vectors for the rapid diffusion of investment fashions that bypass personal risk assessment.

Confirmation Bias in Portfolio Management

Confirmation bias — the tendency to preferentially seek and weight information confirming prior beliefs — has been documented in financial contexts by Friesen and Weller (2006), who showed that analysts update their earnings forecasts by significantly less when new information contradicts their prior estimates compared to when it confirms them. For mutual fund investors, this manifests as selective attention to a fund's positive press releases and positive return months while discounting consecutive negative quarters and persistent peer-relative underperformance.

Sahi (2017) examined confirmation bias alongside seven other behavioral biases among 371 retail investors in Delhi and found that confirmation bias was second only to loss aversion in its frequency of manifestation, with investors showing a strong tendency to seek out opinions matching their prior fund selections and to avoid financial advisors who recommended alternative funds. The study noted that confirmation bias was especially persistent among investors with moderate financial literacy — not the least sophisticated — because partial knowledge enabled rationalizations for ignoring disconfirming evidence.

Pompian and Longo (2004) proposed that confirmation bias interacts with overconfidence in investment contexts: overconfident investors generate more internal forecasts and subsequently apply stronger confirmation filtering to protect those forecasts, creating a compounding effect on suboptimal decision-making. This interaction prediction motivates the present study's joint measurement of all three biases and their combined predictive assessment through multiple regression.

Behavioral Biases among Indian Retail Investors: Regional Dimensions

Waweru, Munyoki and Uliana (2008) adapted behavioral finance survey instruments for Kenyan retail investors — a context with demographic and market development similarities to North Indian retail markets — finding that herd behavior was the most frequently cited behavioral influence on investment decisions, followed by excessive optimism (a form of overconfidence). Their work informed instrument adaptation for subsequent studies in emerging market retail investor contexts.

Jamshidinavid, Chavoshani and Amiri (2012) studied all three biases jointly in Tehran Stock Exchange retail investors and found that herd behavior had the highest predictive power for suboptimal decisions (measured as investment returns below benchmark), followed by overconfidence and then confirmation bias — a finding the present study tests for replication in the Indian Tier-2 city retail investor population. Regional studies specifically addressing UP or Uttarakhand retail investor behavioral biases are absent from the published literature, establishing the research gap that motivates this empirical investigation.

Research Methodology

Survey Design and Data Collection

A descriptive-analytical research design employing primary survey data was adopted. Structured questionnaires were administered to retail mutual fund investors in fourteen cities across Uttar Pradesh and Uttarakhand between June and September 2025. Both Hindi and English versions were made available. Of 390 questionnaires distributed, 374 complete and usable responses were retained after removing 16 incomplete submissions, yielding a response effectiveness rate of 95.9%.

Measurement Scales

The questionnaire comprised five sections. Section A captured demographic and investor profile information including age, gender, education, occupation, monthly income, settlement type, and years of investment experience in mutual funds. Section B measured Overconfidence Bias (OC) through a six-item instrument adapted from Pompian (2012) and Chandra and Kumar (2012), capturing prediction overconfidence, trading frequency self-assessment, self-assessed fund-picking ability, certainty in market timing, perceived informational advantage, and excessive concentration behavior. Cronbach's Alpha for the OC scale was 0.78.

Section C measured Herd Behavior (HB) through six items adapted from Waweru et al. (2008) and Bikhchandani and Sharma (2001), covering: investment decisions based on others' choices, following social media investment advice, acting on WhatsApp group recommendations, imitating colleague investment actions, increasing purchases because peers are buying, and redeeming because others are doing so. Cronbach's Alpha = 0.81. Section D measured Confirmation Bias (CB) through five items adapted from Sahi (2017) and Friesen and Weller (2006): seeking information confirming prior fund choice, avoiding negative news about held funds, ignoring underperformance data, retaining funds against advisor advice, and selectively recalling positive performance episodes. Cronbach's Alpha = 0.76.

Section E captured Suboptimal Investment Decisions (SID) through five items measuring observable behavioral outcomes: redeemed SIPs during a market fall, bought into a fund only because it was a top-performer recently, concentrated investment in a single fund category, held losing funds longer than recommended, and avoided rebalancing for more than twelve consecutive months. Cronbach's Alpha = 0.79. All scales used a five-point Likert format (1 = Strongly Disagree to 5 = Strongly Agree). Respondents were also asked whether they had discontinued any SIP between October 2024 and February 2025 — a period of notable benchmark correction — to provide an objective behavioral anchor for the herd behavior findings.

Bias Classification Threshold

Following the convention applied by Sahi (2017) and Jamshidinavid et al. (2012), respondents with a mean scale score exceeding 3.5 on a given bias scale were classified as exhibiting a high level of that bias, while those scoring 3.5 or below were classified as low/moderate. This threshold corresponds to agreement-leaning responses on the Likert scale and has established precedent in the Indian behavioral finance literature.

Statistical Methods

Data analysis was performed using IBM SPSS Statistics Version 26.0. Descriptive statistics characterized bias prevalence and sample composition. Independent samples t-tests tested H01 (gender difference in OC). One-way ANOVA with Tukey HSD post-hoc tests examined H02 (experience-bias relationship). A Chi-square test and phi coefficient examined H03 (herd behavior-SIP redemption association). Multiple linear regression tested H04, with SID as the dependent variable and OC, HB, CB, investment experience, financial literacy, and gender as predictors. All standard regression assumptions were verified before interpretation.

Data Screening and Preparation

Prior to hypothesis testing, the dataset was screened to ensure analytical integrity. Each returned questionnaire was first examined for completeness and response quality; the sixteen submissions with missing responses on one or more scale items were removed through listwise deletion, leaving 374 fully complete cases with no missing values on any analyzed variable. The retained responses were inspected for careless answering patterns such as straight-lining (identical responses across all items of a construct) and out-of-range entries, and negatively worded items were reverse-coded so that a higher score consistently denoted a stronger presence of the bias. Univariate outliers were assessed by converting item scores to standardized z-scores and flagging absolute values above 3.29; multivariate outliers were screened using Mahalanobis distance evaluated against the chi-square critical value for the relevant degrees of freedom. The few flagged cases did not materially alter the results and were retained to preserve the representativeness of the sample. Finally, the distributional properties of the composite variables were examined: skewness and kurtosis values for all four scales fell within the conventionally accepted range of ±2, supporting the assumption of univariate normality required for the parametric procedures reported below.

Construct Scoring, Reliability and Validity

For each respondent, a composite score was computed for overconfidence, herd behavior, confirmation bias, and suboptimal investment decisions as the arithmetic mean of the constituent Likert items, yielding a continuous index ranging from 1 to 5 for each construct. Internal-consistency reliability was assessed using Cronbach's alpha, and all four scales exceeded the 0.70 threshold recommended by Nunnally (overconfidence $\alpha = 0.78$, herd behavior $\alpha = 0.81$, confirmation bias $\alpha = 0.76$, suboptimal decisions $\alpha = 0.79$), indicating acceptable reliability. Corrected item-total correlations were examined for every scale and exceeded 0.30 for all retained items, confirming that each item contributed coherently to its construct; no item deletion would have produced a meaningful improvement in alpha. Content validity was established through expert review of the instrument by academic specialists in behavioral finance and practicing mutual fund distributors prior to fielding, and all scale items were adapted from previously validated instruments (Pompian, 2012; Chandra & Kumar, 2012; Waweru et al., 2008; Bikhchandani & Sharma, 2001; Sahi, 2017; Friesen & Weller, 2006). To assess construct validity, an exploratory factor analysis using principal-axis factoring with varimax rotation was conducted on the bias items; sampling adequacy was confirmed (Kaiser–Meyer–Olkin measure = 0.83) and Bartlett's test of sphericity was significant ($p < 0.001$), with items loading on their intended factors above 0.50 and negligible cross-loadings, supporting the discriminant distinctness of the three bias constructs.

Measurement of Control Variables

Two control variables were incorporated into the regression model. Investment experience was recorded as completed years of mutual fund investing. Financial literacy was captured through a composite Financial Literacy Score (CFLS) constructed from a set of objective knowledge items adapted from the OECD/INFE financial-literacy framework and the widely used Lusardi–Mitchell items, covering compound interest, the effect of inflation on purchasing power, risk diversification, and the risk–return relationship; each correct response was scored and summed to yield a composite index, with higher values denoting greater financial literacy. Including these two variables as controls allows the incremental predictive contribution of the three behavioral biases to be isolated from the confounding influence of experience and knowledge.

Assumption Testing and Effect-Size Estimation

All inferential tests were two-tailed and evaluated at a significance level of 0.05. For the independent-samples t-tests, Levene's test was used to assess equality of variances and the appropriate statistic reported accordingly; the magnitude of each gender difference was quantified using Cohen's d, which yielded a medium-to-large effect for overconfidence (d = 0.61) and small effects for herd behavior (d = 0.30) and confirmation bias (d = 0.23). For the one-way ANOVAs, homogeneity of variance was verified with Levene's test and the strength of the experience effect was expressed as eta-squared, indicating that investment experience accounted for approximately 15% of the variance in herd behavior ($\eta^2 = 0.15$), 13% in overconfidence ($\eta^2 = 0.13$), and 11% in confirmation bias ($\eta^2 = 0.11$) — medium effects by Cohen's benchmarks — with Tukey HSD tests identifying the specific experience groups that differed. For the chi-square test of the herd–redemption association, all expected cell frequencies exceeded five and the phi coefficient ($\varphi = 0.397$) served as the effect-size measure, denoting a moderate-to-strong association. Before interpreting the multiple regression, its assumptions were examined systematically: linearity was confirmed through inspection of partial-regression plots; independence of residuals was supported by a Durbin–Watson statistic close to 2.0; homoscedasticity was verified from the standardized-residual-versus-predicted scatterplot; the normality of residuals was confirmed via the normal P–P plot; and multicollinearity was ruled out, with all variance-inflation factors below 2.0 (maximum VIF = 1.93) and tolerance values above 0.50. The overall effect size for the model was large (Cohen's $f^2 = 1.10$), and with six predictors and 374 cases the analysis comfortably exceeded the minimum sample size of 98 implied by Green's rule ($N \geq 50 + 8k$), providing ample statistical power.

Results and Analysis

Sample Profile

Table 1: Demographic and Investor Profile of the Sample (N = 374)

Demographic Variable	Category	Frequency (%)
Gender	Male	261 (69.8%)
	Female	113 (30.2%)
Age Group	18–25 Years	43 (11.5%)
	26–35 Years	126 (33.7%)
	36–45 Years	110 (29.4%)
	46–55 Years	68 (18.2%)
	Above 55 Years	27 (7.2%)

Education	Up to Class 12th	33 (8.8%)
	Graduate	164 (43.9%)
	Post-Graduate	141 (37.7%)
	Professional Degree	36 (9.6%)
Investment Experience	Less than 2 Years	68 (18.2%)
	2–5 Years	147 (39.3%)
	5–10 Years	107 (28.6%)
	More than 10 Years	52 (13.9%)

The sample is demographically well-spread across age and occupational categories. A notable feature is the investment experience distribution: 57.5% of respondents have five years or fewer of mutual fund investment experience — classifying them as relatively recent market entrants. This composition is consistent with the AMFI-documented surge in new investor registrations across B30 geographies post-2020 and means the sample captures a population segment where behavioral biases are likely to be most acute and most consequential.

Bias Prevalence in the Sample

Table 2: Prevalence of Behavioral Biases among Retail Investors (N = 374)

Behavioral Bias	Mean Score	Std. Dev.	Cronbach's α	High Bias N	High Bias %
Overconfidence Bias (OC)	3.47	0.79	0.78	175	46.8%
Herd Behavior (HB)	3.62	0.74	0.81	197	52.7%
Confirmation Bias (CB)	3.38	0.82	0.76	154	41.2%
All Three Biases Present Simultaneously	—	—	—	91	24.3%

Herd behavior emerges as the most prevalent bias in this population, with a mean score of 3.62 and 52.7% of investors classified as high-herd. This finding is consistent with the social information environment characteristic of UP and Uttarakhand, where community-based decision-making norms and the recent explosion of WhatsApp investment advisory groups create structural conditions favorable to herding. Overconfidence is the second most prevalent bias (46.8%), and confirmation bias the third (41.2%). The co-occurrence of all three biases in 24.3% of the sample highlights a subgroup of investors who face compound behavioral risk — their investment decisions are simultaneously distorted by overestimation of own ability, excessive social influence, and selective information processing.

Top Triggers of Herd Behavior

Table 3: Primary Triggers of Herd Behavior — Top 5 Cited Sources (N = 374, Multiple Responses Allowed)

Trigger of Herd Behavior	Frequency	% of Respondents
Social Media Investment Advice (YouTube, Instagram, Twitter/X)	237	63.5%
WhatsApp Investment Groups / Telegram Channels	203	54.2%
Peer / Colleague Investment Actions	180	48.1%
Fund Distributor / MFD Recommendations During Trending Market	143	38.2%
News Channels and Financial Television Programming	118	31.6%

Social media platforms emerge as the dominant herd trigger (63.5%), followed closely by WhatsApp and Telegram investment communities (54.2%). The scale of these digital herding channels is a distinctly contemporary finding: in earlier generations of mutual fund investor surveys from this region, broker and MFD recommendations and peer word-of-mouth dominated as influence channels. The displacement of traditional channels by digital platforms — which offer lower-friction, high-frequency, algorithm-amplified investment recommendations with no suitability assessment — represents a qualitative shift in the herd behavior risk profile of retail investors in UP and Uttarakhand. Peer and colleague influence (48.1%) reflects the enduring role of social reference groups in these states' investor culture.

Gender Differences in Bias Levels (H01)

Table 4: Independent Samples t-Test — Behavioral Biases by Gender

Bias	Male Mean (N=261)	Male SD	Female Mean (N=113)	Female SD	t-Statistic	p-Value
Overconfidence (OC)	3.61	0.74	3.14	0.82	**5.69*** **	< 0.001
Herd Behavior (HB)	3.48	0.81	3.71	0.69	**-2.84** **	0.005
Confirmation Bias (CB)	3.29	0.77	3.47	0.84	**-2.17***	0.031

Significance: *** p < 0.001 | ** p < 0.01 | * p < 0.05 — H01 Rejected for OC (Males significantly more overconfident)

The t-test results produce a nuanced gender picture across the three biases. Male investors are significantly more overconfident (mean = 3.61) than females (mean = 3.14), with a large mean difference of 0.47 confirmed at the 0.1% significance level ($t = 5.69$, $p < 0.001$). H01 is rejected for overconfidence. This finding replicates the well-established male-overconfidence pattern from Barber and Odean (2001) in the UP-Uttarakhand retail investor context. However, the gender pattern reverses for herd behavior and confirmation bias: female investors exhibit significantly higher herding (3.71 vs 3.48, $p = 0.005$) and slightly higher confirmation bias (3.47 vs 3.29, $p = 0.031$) than males. The female herding finding may reflect the greater reliance on social reference networks for investment decisions among female investors who have had comparatively less exposure to independent financial training — a structural explanation rooted in education and information access rather than cognitive capacity.

Effect of Investment Experience on Bias Levels (H02)

Table 5: One-Way ANOVA — Behavioral Bias Scores by Investment Experience Group

Bias	< 2 Yrs	2–5 Yrs	5–10 Yrs	> 10 Yrs	F Statistic	p-Value

	Mean	Mean	Mean	Mean		
Overconfidence (OC)	3.78	3.54	3.37	2.94	**18.43*** **	< 0.001
Herd Behavior (HB)	3.91	3.64	3.29	2.87	**22.17*** **	< 0.001
Confirmation Bias (CB)	3.62	3.41	3.18	2.76	**14.86*** **	< 0.001
Post-Hoc Tukey HSD: All adjacent experience group pairs significantly different (p < 0.05) for all three biases — H02 Rejected						

The ANOVA results reveal a remarkably consistent and monotonically declining pattern across all three biases as investment experience increases. Herd behavior shows the steepest decline — from a mean of 3.91 among investors with less than two years' experience to 2.87 among those with over ten years (a reduction of 1.04 scale points), followed by overconfidence (3.78 to 2.94, reduction of 0.84) and confirmation bias (3.62 to 2.76, reduction of 0.86). Post-hoc Tukey HSD tests confirm that differences between all adjacent experience groups are statistically significant for all three biases. H02 is rejected: investment experience substantially reduces herd behavior.

This experience-bias gradient has an important interpretation: it suggests that market learning — exposure to actual investment outcomes across market cycles — is a natural debiasing mechanism. Investors who have experienced a full market cycle, including a significant correction, have direct evidence that following the crowd produces poor outcomes and that panic redemptions destroy wealth. This learning-based debiasing is not guaranteed by time alone, however — it requires actual exposure to outcome feedback, which is why financial literacy interventions that simulate cycle experience through case studies and historical scenario presentations may accelerate the debiasing process for newer investors.

Herd Behavior and SIP Redemption During Market Correction (H03)

Table 6: Herd Behavior Group vs. SIP Redemption During Oct 2024 – Feb 2025 Market Correction

Herd Behavior Group	N	SIP Redeemed / Paused (%)	SIP Continued (%)
High Herd Behavior (Mean > 3.5)	197	**58.4% (115)**	41.6% (82)
Low/Moderate Herd Behavior (Mean ≤ 3.5)	177	19.7% (35)	**80.3% (142)**
Chi-Square = 58.74 | df = 1 | p < 0.001 | Phi Coefficient = 0.397 (Moderate-Strong Effect) — H03 Rejected			

The herd behavior-SIP redemption association provides the study's most compelling behavioral finance finding. Among high-herd investors, 58.4% redeemed or paused at least one SIP during the October 2024 – February 2025 market correction period, compared to only 19.7% of low-herd investors — a nearly three-fold difference. The Chi-square test ($\chi^2 = 58.74$, $p < 0.001$) confirms this association is statistically highly significant, and the phi coefficient of 0.397 indicates a moderate-to-strong practical effect size. H03 is rejected.

The economic significance of this finding is considerable. An investor who pauses a monthly SIP of INR 5,000 for six months during a correction — precisely the period when rupee-cost averaging provides the greatest benefit through unit accumulation at depressed prices — forgoes approximately 36 units that would be purchased at an assumed NAV of INR 83 (a representative mid-cap fund NAV during the correction trough). At the subsequent recovery NAV of INR 112 (eighteen months later), these 36 foregone units represent a wealth cost of approximately INR 4,032 per INR 5,000 monthly SIP — an opportunity cost that compounds dramatically for investors with longer investment horizons.

Correlation Matrix — Bias Inter-Relationships and SID

Table 7: Pearson Correlation Matrix — Behavioral Biases and Suboptimal Investment Decisions

Variable	OC	HB	CB	SID
Overconfidence (OC)	1.000	0.381**	0.447**	0.547**
Herd Behavior (HB)	0.381**	1.000	0.412**	0.593**
Confirmation Bias (CB)	0.447**	0.412**	1.000	0.481**

Suboptimal Investment Decisions (SID)	0.547**	0.593**	0.481**	1.000
**** Correlation significant at the 0.01 level (2-tailed)**				

The correlation matrix reveals that all three biases are positively and significantly correlated with each other, consistent with the hypothesis that they co-manifest in the same individual. The OC-CB correlation of r = 0.447 is notably the strongest inter-bias relationship, supporting Pompian and Longo's (2004) theoretical prediction that overconfident investors apply stronger confirmation filtering. All three biases correlate significantly with SID, with herd behavior showing the strongest relationship (r = 0.593), followed by overconfidence (r = 0.547) and confirmation bias (r = 0.481). The moderate inter-bias correlations (ranging from 0.381 to 0.447) confirm that the three constructs are related but sufficiently distinct to warrant separate measurement rather than collapsing into a single composite bias score.

Multiple Regression — Predictors of Suboptimal Investment Decisions (H04)

Table 8: Multiple Linear Regression — Predictors of Suboptimal Investment Decisions (SID)

Predictor Variable	B (Unstd.)	Std. Err.	Beta (β)	t-Value	p	VIF
(Constant)	0.741	0.193	—	3.84	0.000	—
Herd Behavior (HB) Score	0.421	0.064	**0.374**	6.58	0.000	1.72
Overconfidence (OC) Score	0.348	0.061	**0.318**	5.70	0.000	1.68
Confirmation Bias (CB) Score	0.219	0.057	**0.221**	3.84	0.000	1.81
Investment Experience (Years)	-0.187	0.043	**-0.184**	-4.35	0.000	1.59
Financial Literacy Score (CFLS)	-0.148	0.047	**-0.163**	-3.15	0.002	1.93
Gender (Male = 1)	-0.079	0.038	-0.087	-2.08	0.038	1.31
R^2 = 0.524 | Adjusted R^2 = 0.516 | F (6, 367) = 67.49 | $p < 0.001$ | Max VIF = 1.93 — Multicollinearity: Not a Concern						

The regression model explains 52.4% of the variance in SID (Adjusted R^2 = 0.516) — exceptionally strong explanatory performance for a behavioral social science model. The overall model F-statistic of 67.49 (p <

0.001) confirms joint significance. All VIF values are comfortably below 5 (maximum 1.93), ruling out multicollinearity concerns. H04 is rejected: all three behavioral biases are significant positive predictors of suboptimal investment decisions even after controlling for experience and financial literacy.

Herd behavior is the single strongest predictor ($\beta = 0.374$, $p < 0.001$), followed by overconfidence ($\beta = 0.318$, $p < 0.001$) and confirmation bias ($\beta = 0.221$, $p < 0.001$). This ordering replicates the Jamshidinavid et al. (2012) finding from Tehran Stock Exchange retail investors and carries particular significance in the UP-Uttarakhand context given the documented dominance of social media and WhatsApp herding triggers in this population. Importantly, investment experience ($\beta = -0.184$, $p < 0.001$) and financial literacy ($\beta = -0.163$, $p = 0.002$) are significant negative predictors — investors with more experience and higher financial literacy make proportionally fewer suboptimal decisions, even when behavioral biases are present, suggesting that these variables partially compensate for bias effects. The negative gender coefficient ($\beta = -0.087$, $p = 0.038$) indicates that male investors make marginally more suboptimal decisions than females after all controls — paradoxically driven by their higher overconfidence offsetting females' greater herding.

Discussion

Comparison with Prior Empirical Findings

The relative ordering of the three biases as predictors of suboptimal decisions — herd behavior first, overconfidence second, confirmation bias third — closely replicates Jamshidinavid, Chavoshani and Amiri (2012), who reported the identical ranking among Tehran Stock Exchange retail investors, and it aligns with Waweru, Munyoki and Uliana (2008), for whom herding was the most frequently cited behavioral influence in an emerging-market setting. This convergence across three distinct emerging markets — Iran, Kenya, and now North India — strengthens the external validity of the proposition that social herding, rather than individual overconfidence, is the dominant behavioral risk in markets characterized by uneven information distribution and dense social networks. The pattern contrasts, however, with the developed-market literature epitomised by Barber and Odean (2001) and Odean (1998), in which overconfidence-driven excessive trading is treated as the pre-eminent source of retail underperformance. The divergence is theoretically coherent: the information-cascade conditions modeled by Bikhchandani and Sharma (2001) — many relatively uninformed participants observing one another under high uncertainty — are more fully realised in a young, digitally networked investor base than in the mature brokerage populations that Barber and Odean studied.

The gender findings both confirm and extend the established literature. The significantly higher overconfidence among male investors (d = 0.61) reproduces the robust "boys will be boys" pattern documented by Barber and Odean (2001) and corroborated in Indian samples by Chandra and Kumar (2012) and Raut and Das (2015). The countervailing result — that female investors exhibit significantly higher herd behavior — has been less prominent in the Western literature, which has more often emphasized women's lower trading frequency and greater caution. It is, however, consistent with an interpretation in which the same underlying tendency toward greater reliance on external and social sources of information manifests as caution in one context and as herding in another: where trusted independent information is scarce, deference to a visible social consensus becomes the default heuristic. This reframes the common assumption that female investors are uniformly "less biased," suggesting instead that the bias profile is gendered in composition rather than simply lower in magnitude.

The position of confirmation bias as the weakest of the three predictors, coupled with its strong correlation with overconfidence (r = 0.447, the largest inter-bias correlation observed), provides direct empirical support for the compounding mechanism proposed by Pompian and Longo (2004), whereby overconfident investors generate more private forecasts and then apply stronger confirmatory filtering to defend them. That confirmation bias ranks lower here than in Sahi (2017) — where it was second only to loss aversion among Delhi investors — is attributable partly to a difference in the outcome construct (the present study anchors bias to observable suboptimal behaviors and SIP redemption rather than to financial satisfaction) and partly to the pronounced amplification of herd behavior in a sample far more exposed to social-media and messaging-group influence than earlier Indian survey populations.

The monotonic decline of all three biases with investment experience is consistent with the experiential-learning account of debiasing, and it echoes Feng and Seasholes (2005), who found that trading experience substantially attenuates — though does not fully eliminate — behavioral biases among individual investors. The persistence of non-trivial bias levels even among the most experienced group in the present sample (all group means remaining above 2.7) supports their qualified conclusion that experience mitigates rather than eradicates bias, and cautions against treating time in the market as a complete substitute for structured investor education. The observation that herd behavior declines most steeply with experience is intuitive within the cascade framework: investors who have personally witnessed a consensus reverse are precisely those most likely to discount the next apparent consensus.

Finally, the behavioral anchor at the heart of this study — the near three-fold higher rate of SIP redemption among high-herd investors during the October 2024–February 2025 correction — operationalises, in a realeconomy setting, the fragile-equilibrium prediction of Bikhchandani and Sharma (2001) and the social-media overreaction cycle documented by Han, Tang and Yang (2022). Where prior studies largely inferred herding from aggregate fund-flow data or self-reported attitudes, the present design links a validated herd-behavior score to an objective, welfare-relevant action taken at an inopportune moment in the market cycle, thereby narrowing the gap between attitudinal measurement and observed behavior that the behavioral-finance literature has repeatedly identified as a limitation.

The finding that herd behavior is the most prevalent bias (52.7%) and the strongest predictor of suboptimal investment decisions in this population is not merely an academic result — it identifies a specific mechanism through which retail investor welfare is being impaired in UP and Uttarakhand's rapidly growing mutual fund market. The social media trigger data are especially telling: 63.5% of investors cite social media investment advice as a primary herding trigger, and 54.2% cite WhatsApp investment communities. These channels operate without SEBI's suitability assessment requirements, without the relationship accountability of a registered MFD, and with algorithmic incentives toward engagement-maximizing content — which is disproportionately content about short-term market events, top-performing schemes, and trading opportunities rather than long-term SIP discipline.

The SIP redemption finding — that 58.4% of high-herd investors discontinued SIPs during the 2024-25 correction versus 19.7% of low-herd investors — makes the economic stakes of herd behavior concrete. It also identifies a precise, measurable, and policy-addressable behavioral failure: the inability to maintain investment commitments during periods of social-media-amplified negative sentiment. MFDs and AMC digital platforms could design specific behavioral nudges — automated SIP continuation reminders citing long-term performance data, personalised 'your SIP history' notifications showing units accumulated during past corrections, and lock-in commitment devices — targeted specifically at the correction period to reduce herd-driven redemptions.

The male-overconfidence finding replicates an extremely robust cross-cultural pattern and its consequences in this region may be particularly acute given the male-dominated investor composition (69.8%). Overconfident male investors in UP and Uttarakhand who trade excessively in direct equity rather than maintaining SIP-based mutual fund portfolios incur alpha-destroying transaction costs and tax consequences. For MFDs serving this population, recognizing male overconfidence as a systematic client risk — not a compliment to be reinforced — and building counter-overconfidence advisory scripts into client communication is both commercially and ethically advisable.

The experience-bias gradient suggests that the behaviorally highest-risk cohort in this investor population are recent entrants — the 18.2% of respondents with less than two years of experience, who entered the market primarily during the 2020-2024 bull run and have not yet experienced a full market cycle. This cohort combines maximum herd behavior susceptibility (mean HB = 3.91) with maximum overconfidence (mean OC = 3.78) at precisely the moment when they are making formative portfolio construction decisions. Targeted investor education interventions — specifically simulating bear market scenarios and teaching the mathematics of SIP continuation during corrections — are most needed for this sub-population.

Conclusion

This study provides the first region-specific empirical evidence on the prevalence and investment consequences of overconfidence, herd behavior, and confirmation bias among retail mutual fund investors in Uttar Pradesh and Uttarakhand. Herd behavior is the most prevalent bias at 52.7%, with social media and WhatsApp communities identified as its primary contemporary triggers. All three biases significantly and independently predict suboptimal investment decisions in a regression model explaining over 52% of variance.

The three-fold higher rate of SIP redemption during a market correction among high-herd versus low-herd investors provides a concrete, economically meaningful demonstration of how behavioral bias directly translates into investor wealth destruction. The experience-based debiasing effect — all three biases declining monotonically with investment experience — suggests that market learning is a natural corrective mechanism, but one that takes multiple years and market cycles to operate. Investor education interventions that accelerate this cycle experience through scenario-based learning can therefore produce meaningful bias reduction in newer investor cohorts.

For AMCs, MFDs, and SEBI, the practical priorities are clear: develop WhatsApp and social-media-specific investor protection frameworks that bring the same suitability and disclosure standards applied to registered advisory channels; design SIP-continuation behavioral nudges specifically calibrated for market correction periods; and target male overconfidence and female herding with gender-tailored communication strategies. For academic researchers, the robust model fit (Adjusted $R^2 = 0.516$) validates the joint behavioral bias measurement framework for application in other state-level investor populations across India.

Limitations

Several limitations qualify the interpretation of these findings. First, all bias measures are self-reported, creating potential social desirability bias — respondents may under-report herding because it is perceived as a sign of naivety. Future research should complement self-reported scales with objective trading data from demat accounts or AMC transaction records, which would provide a behaviorally validated anchor. Second, the SIP redemption data covering October 2024 to February 2025 is based on respondent recall and may be subject to retrospective misattribution. Third, the cross-sectional design prevents causal inference about the direction of the experience-bias relationship — it is theoretically possible that less-biased investors accumulate more investment experience (survival bias), though the monotonic pattern across all three biases makes this the less parsimonious explanation. Fourth, WhatsApp group membership and social media consumption frequency were captured as dichotomous triggers rather than continuous intensity measures, limiting the precision of digital herding channel analysis. Future studies should incorporate detailed social media consumption metrics to quantify the dose-response relationship between digital information exposure and herding intensity among retail investors in this region.

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