WHICH BIASES MATTER MOST? PRIORITIZING BEHAVIORAL INTERVENTIONS FOR RETAIL INVESTORS THROUGH IMPORTANCE-PERFORMANCE MAP ANALYSIS

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ABSTRACT

Understanding which cognitive biases most urgently demand managerial attention is a challenge that statistical significance alone cannot resolve. This study employs Importance-Performance Map Analysis (IPMA) within a Partial Least Squares Structural Equation Modeling (PLS-SEM) framework to produce a priority map of behavioral biases and Theory of Planned Behavior (TPB) constructs affecting retail investors' investment intentions. Using data from 364 retail investors in Delhi-NCR, India, the model treats behavioral biases as a reflective second-order construct comprising seven sub-dimensions: overconfidence, anchoring, availability bias, loss aversion, mental accounting, representativeness, and regret aversion alongside attitude, subjective norms, and perceived behavioral control as structural predictors. IPMA reveals that overconfidence (importance = 0.209, performance = 66.03) and loss aversion (importance = 0.175, performance = 55.46) are the highest-priority intervention targets, exhibiting strong structural influence on investment intention yet operating below the sample's average performance benchmark. Regret aversion and anchoring constitute a secondary priority cluster, while perceived behavioral control, though structurally meaningful (β = 0.199), already performs well, implying diminishing returns to further investment in self-efficacy building. Subjective norms are both structurally negligible and already high-performing, placing them firmly in the low-priority quadrant. The study advances the IPMA literature by providing a validated, resource-allocation-oriented framework for debiasing retail investors in emerging economies, offering actionable guidance for financial advisors, regulators, and fintech platform developers.

Keywords: *IPMA; behavioral biases; investment intention; PLS-SEM; overconfidence; loss aversion; retail investors; India; Theory of Planned Behavior*

1. INTRODUCTION

India's retail investment landscape has undergone a structural transformation. Between 2020 and 2025, the number of active demat accounts rose from approximately 40 million to over 175 million, driven by the proliferation of mobile trading platforms, declining brokerage costs, and post-pandemic financial awareness campaigns (SEBI, 2025; Chandani et al., 2025). Yet the democratization of market access has not translated into consistently rational decision-making. Retail investors continue to buy past winners, hold losing positions far beyond any defensible fundamental threshold, trade excessively on self-assessed expertise, and anchor their expectations to irrelevant historical price points (Barber & Odean, 2001; Baker & Nofsinger, 2002). These patterns represent systematic cognitive biases that behavioral finance has documented extensively, but that practitioners have struggled to remediate effectively.

A central difficulty is one of prioritization. Behavioral finance identifies numerous distinct biases, and the theory of planned behavior (TPB; Ajzen, 1991) identifies multiple social-cognitive antecedents of intention. Knowing that overconfidence, loss aversion, and perceived behavioral control each predict investment intention does not, by itself, tell a financial advisor, a regulator, or a fintech product manager where to concentrate limited intervention resources. This is precisely the problem that Importance-Performance Map Analysis (IPMA) is designed to solve. IPMA, developed within PLS-SEM by Ringle and Sarstedt (2016), simultaneously evaluates the structural importance of each predictor, derived from its total effect on the target construct, and its current performance level, rescaled to a 0–100 metric. Constructs that are both highly important and currently underperforming represent the highest-priority targets for improvement, since improving them yields the greatest incremental benefit to the outcome of interest.

Despite its analytical appeal, IPMA remains conspicuously underemployed in behavioral finance and investment-intention research (Ringle & Sarstedt, 2016; Martínez-López et al., 2020). Existing studies in this domain establish the significance of predictors through path coefficients and bootstrapped confidence intervals but rarely extend the analysis to generate managerially actionable priority rankings. This study addresses that gap. Drawing on a sample of 364 retail investors from Delhi-NCR and a rigorously validated second-order PLS-SEM model, it applies IPMA to rank behavioral bias sub-dimensions and TPB antecedents in terms of their urgency for targeted intervention. The findings contribute a novel, empirically grounded resource-allocation framework that is directly applicable to investor education, regulatory policy design, and the development of behavioral-nudge features on fintech platforms.

The remainder of this paper proceeds as follows. Section 2 establishes the theoretical background and study hypotheses. Section 3 describes the research methodology. Section 4 reports measurement model results, structural model findings, and IPMA outputs at both construct and indicator levels. Section 5 discusses the theoretical and practical implications. Section 6 offers conclusions and directions for future research.

2. THEORETICAL BACKGROUND AND HYPOTHESES

2.1 Behavioral Biases in Investment Decision-Making

Behavioral finance challenges the efficient market hypothesis (Fama, 1970) by documenting persistent and systematic deviations from rationality among individual investors (Barberis & Thaler, 2003; Shiller, 2003). These deviations are organized around two broad theoretical traditions. First, Kahneman and Tversky's (1974) heuristics-and-biases program identifies simplification strategies: anchoring, availability, and representativeness, that produce predictable judgment errors. Second, Prospect Theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) explains anomalies related to gains and losses, including loss aversion, the disposition effect, and regret aversion.

Overconfidence leads investors to overestimate the accuracy of their private information and the quality of their forecasting ability, generating excessive trading, insufficient diversification, and inflated return expectations (Barber & Odean, 2001; Glaser & Weber, 2007; Merkle, 2017). Loss aversion ,the finding that losses loom psychologically roughly twice as large as equivalent gains , produces reluctance to realize paper losses, resulting in the well-documented disposition effect (Kahneman & Tversky, 1979; Ben-David & Hirshleifer, 2012; Frydman & Rangel, 2014). Anchoring bias tethers investors' price expectations to reference points such as purchase prices or 52-week highs, impairing the integration of new information (Furnham & Boo, 2011; Jain et al., 2023). Regret aversion ,the avoidance of choices that might produce counterfactual regret ,systematically biases investors toward inaction or toward socially normalized positions (Zeelenberg, 1999; Kaur & Kaushik, 2023). Availability bias inflates the perceived likelihood of salient, recent, or emotionally vivid events, distorting probability estimates and risk perception (Tversky & Kahneman, 1973; Waweru et al., 2008). Representativeness induces investors to categorize assets by superficial similarity to familiar patterns, producing momentum chasers and gambler's-fallacy errors (De Bondt & Thaler, 1985; Nofer et al., 2021). Finally, mental accounting fragments wealth into separate cognitive sub-accounts, violating the fungibility principle and producing suboptimal portfolio decisions (Thaler, 1999; Bhatia & Kumar, 2023).

In the present model, these seven biases are treated as first-order reflective sub-constructs converging on a single second-order Behavioral Biases (BB) construct, consistent with the hierarchical component modeling approach advocated by Hair et al. (2021) and van Riel et al. (2017). This operationalization captures the shared predisposition underlying individual biases while preserving the sub-dimensional granularity necessary for IPMA. The hypothesis is that BB positively influences both attitude toward investing and investment intention directly.

2.2 Theory of Planned Behavior

The Theory of Planned Behavior (Ajzen, 1991) proposes that behavioral intention ,the motivational precursor of action ,is a function of three antecedents: attitude (the individual's overall evaluative judgment of performing the behavior), subjective norms (perceived social pressure from significant others), and perceived behavioral control (the individual's sense of ability and autonomy over the behavior). Decades of meta-analytic evidence confirm the model's broad predictive validity across domains including health behavior, consumer choice, and financial decision-making (Armitage & Conner, 2001; McEachan et al., 2011). In investment contexts specifically, TPB has been applied to stock market participation (Gopi & Ramayah, 2007), online investment behavior (Bashir et al., 2013), and mutual fund selection (Aren & Zengin, 2016), consistently finding meaningful contributions from attitude and perceived behavioral control, with more variable support for subjective norms (Alleyne & Broome, 2011; Raut, 2020).

The present study extends prior TPB applications by integrating behavioral biases as a structural antecedent to both attitude and investment intention, and by employing IPMA to generate a comparative priority ranking across the combined set of TPB and behavioral finance predictors. The key hypotheses are: (H1) behavioral biases positively influence investment intention; (H2) attitude positively influences investment intention; (H3) subjective norms positively influence investment intention; (H4) perceived behavioral control positively influences investment intention; (H5) behavioral biases positively influence attitude; and (H6) attitude mediates the effect of behavioral biases on investment intention.

2.3 IPMA as an Analytical Extension

IPMA was introduced by Ringle and Sarstedt (2016) as a practical extension of PLS-SEM that shifts the analytical focus from statistical significance to managerial relevance. A predictor's importance is its total effect on the target construct ,capturing both direct and indirect influence paths. Its performance is the rescaled mean of its constituent indicators: Performance = [(raw mean − minimum) / (maximum − minimum)] × 100. By plotting importance on the horizontal axis and performance on the vertical axis, and partitioning the space around the sample means, IPMA generates four quadrants: (I) high importance/low performance ,the critical action zone; (II) high importance/high performance ,sustain and protect; (III) low importance/low performance ,low urgency; and (IV) low importance/high performance ,potential over-investment. Several recent studies have demonstrated IPMA's value in consumer behavior (Martínez-López et al., 2020), hospitality (Akter et al., 2022), and digital finance (Singh et al., 2025), but its application to behavioral bias prioritization in retail investment settings remains novel.

3. METHODOLOGY

3.1 Research Design and Sample

A quantitative, cross-sectional survey design was adopted. The target population comprised individual retail investors who actively traded in Indian equity or mutual fund markets. Data collection was conducted in the Delhi-NCR region ,India's largest urban financial hub ,using a combination of purposive and snowball sampling. Purposive sampling ensured respondents had direct investment experience; snowball referrals extended reach through brokerage forums, online trading communities, and professional financial networks, consistent with established protocols for accessing specialist investor populations (Saunders et al., 2019; Memon et al., 2025). A total of 390 responses were collected. After removing 26 responses due to excessive missing data, straight-lining patterns, and implausible response times (Memon et al., 2024; Amusa & Hossana, 2024), 364 usable responses were retained for analysis.

The final sample was predominantly male (61.8%), concentrated in the 26–35-year age bracket (37.4%), and well-educated, with 71.2% holding graduate or postgraduate qualifications. A majority were salaried employees (42.6%), and 65.4% had between one and six years of investment experience. This profile is broadly representative of Delhi-NCR's active retail investor base, as documented in recent SEBI (2025) and IBEF (2024) surveys. The sample of 364 exceeds the minimum requirement for PLS-SEM derived from the 10-times rule applied to the construct with the largest number of incoming structural paths (Hair et al., 2021).

3.2 Measurement Instrument

All constructs were measured using multi-item, five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree) adapted from validated instruments in the behavioral finance and TPB literature. Anchoring (4 items) was adapted from Kaustia et al. (2008) and Jain et al. (2023). Availability bias (3 items), representativeness (3 items), overconfidence (3 items), mental accounting (3 items), and regret aversion (3 items) were adapted from Bashir et al. (2020), Talwar et al. (2021), and Mer and Vishwakarma (2023). Loss aversion (4 items) followed Barberis and Thaler (2003) and Hoffmann et al. (2013). Attitude (3 items), subjective norms (3 items), and perceived behavioral control (3 items) were adapted from Ajzen (1991), Raut (2020), and Che Hassan et al. (2024). Investment intention (4 items) followed East (1993), Raut (2020), and Srivastava et al. (2025). Content validity was established through a panel review by academic experts in behavioral finance and investment psychology prior to a pilot test on 35 investors (Hair et al., 2021).

3.3 Analytical Strategy

PLS-SEM was employed using SmartPLS 4.0 (Ringle et al., 2022), consistent with the study's theory-extending objectives, the presence of a second-order reflective construct, and the emphasis on predictive relevance rather than confirmatory fit (Hair et al., 2021). The second-order Behavioral Biases construct was specified via a two-stage hierarchical component model (HCM): latent variable scores from the seven first-order constructs served as indicators of the second-order construct, preserving parsimony while capturing the shared variance across bias sub-dimensions (van Riel et al., 2017; Sarstedt et al., 2019).

Assessment followed the two-step procedure recommended by Hair et al. (2021). The outer (measurement) model was evaluated for indicator reliability (loadings $\geq$ 0.70), internal consistency (Cronbach's α, Dijkstra-Henseler's ρa, and Jöreskog's ρc > 0.70), convergent validity (AVE $\geq$ 0.50), and discriminant validity via the HTMT criterion (< 0.85; Henseler et al., 2015). The structural model was then assessed for multicollinearity (VIF < 5.0), path coefficients, R^2 values, and hypothesis significance using bias-corrected bootstrapping with 10,000 subsamples (Hair et al., 2022). IPMA was subsequently applied with investment intention as the target construct, decomposing total effects into direct and indirect components and rescaling indicator means to a 0–100 performance metric (Ringle & Sarstedt, 2016).

4. RESULTS

4.1 Measurement Model Assessment

Table 1 presents the reliability and validity indices for the second-order measurement model. All Cronbach's alpha values exceeded 0.70, ranging from 0.714 (Behavioral Biases) to 0.905 (Investment Intention). Dijkstra-Henseler's ρa and Jöreskog's ρc both surpassed the threshold of 0.70 for each construct, confirming internal consistency and composite reliability. Average Variance Extracted exceeded 0.50 for all constructs, establishing convergent validity (Fornell & Larcker, 1981). HTMT ratios remained below the 0.85 threshold across all construct pairs (maximum = 0.808 for BB-Int and BB-PBC pairs), confirming discriminant validity (Henseler et al., 2015; Franke & Sarstedt, 2019). Individual indicator loadings in both the first-order and second-order models exceeded 0.80, providing further evidence of strong indicator reliability.

Table 1: Reliability and Validity Statistics -Second-Order Measurement Model

Construct	**α**	**ρa**	**ρc**	**AVE**	**Max HTMT**
Attitude (AT)	0.834	0.835	0.900	0.754	0.766
Behavioral Biases (BB)	0.714	0.759	0.796	0.512	0.808
Investment Intention (Int)	0.905	0.931	0.933	0.778	0.808
Perceived Behavioral Control (PBC)	0.897	0.898	0.936	0.830	0.798
Subjective Norms (SN)	0.882	0.883	0.927	0.808	0.798

Note. *α = Cronbach's alpha; ρa = Dijkstra-Henseler's composite reliability; ρc = Jöreskog's composite reliability; AVE = Average Variance Extracted; Max HTMT = highest HTMT ratio involving the construct. All indicators exceeded loading thresholds of 0.70 (Hair et al., 2021). Discriminant validity confirmed: all HTMT < 0.85 (Henseler et al., 2015).*

4.2 Structural Model Results

Inner VIF values ranged from 1.00 to 2.37, well below the threshold of 5.0, ruling out collinearity concerns. Table 2 presents the direct and indirect path results estimated via bias-corrected bootstrapping (10,000 iterations). Behavioral Biases (BB) emerged as the strongest predictor of Investment Intention (β = 0.441, t = 7.022, p < .001), followed by Perceived Behavioral Control (β = 0.199, t = 3.835, p < .001) and Attitude (β = 0.159, t = 3.291, p =

.001). Subjective Norms did not reach statistical significance (β = 0.088, t = 1.584, p = .113), failing to meet the threshold of t > 1.96 (Hair et al., 2022). BB was a strong predictor of Attitude (β = 0.620, t = 18.373, p < .001), confirming that cognitive biases shape evaluative dispositions toward investing. The combined model explained 58.6% of the variance in Investment Intention (R^2 = 0.586) and 38.5% of the variance in Attitude (R^2 = 0.385). Attitude partially mediated the BB-Investment Intention relationship (β = 0.149, t = 4.449, p < .001), confirming Hypothesis H6. According to Cohen's (1988) conventions, these R^2 values represent moderate to substantial predictive power.

Table 2: Structural Path Coefficients and Hypothesis Testing

Path	β	SD	t	p	R²	Decision
BB → Investment Intention	0.441	0.063	7.022	<.001	0.586	Supported
Attitude → Investment Intention	0.159	0.048	3.291	.001		Supported
PBC → Investment Intention	0.199	0.052	3.835	<.001		Supported
Subjective Norms → Investment Intention	0.088	0.056	1.584	.113		Not Supported
BB → Attitude	0.620	0.034	18.373	<.001	0.385	Supported
BB → AT → Investment Intention (indirect)	0.149	0.034	4.449	<.001		Supported

Note. *β = standardized path coefficient; SD = standard deviation; t = t-statistic; p = two-tailed p-value. Bias-corrected bootstrapping, 10,000 iterations. R² reported for endogenous constructs only. VIF range: 1.00–2.37.*

4.3 IPMA -Construct Level

Table 3 reports construct-level IPMA results for the target construct Investment Intention. Behavioral Biases holds the highest importance score by a wide margin (total effect = 0.441), while its average rescaled performance across sub-dimensions (= 63.24) falls below the sample average of 65.86, placing it firmly in the high-importance/moderate-performance quadrant ,the critical action zone (Ringle & Sarstedt, 2016). Perceived Behavioral Control occupies the sustain zone, combining moderate structural importance (total effect = 0.199) with above-average performance (71.02), suggesting that Indian retail investors already possess reasonable financial self-efficacy that does not require urgent enhancement. Attitude sits in the moderate-importance/moderate-performance zone, indicating that some improvement in attitudinal formation processes could yield meaningful gains in investment intention, though not at the same urgency as behavioral biases. Subjective Norms remain in the low-priority quadrant, combining negligible structural importance (0.088) with high performance (73.88), consistent with evidence from emerging markets that internalized cognitive and efficacy factors dominate social normative pressures in investment decision-making (Agustin et al., 2023; Tran et al., 2025).

Table 3: Construct-Level IPMA Results -Target: Investment Intention

Construct	Importance	Performance	Quadrant Classification
Behavioral Biases (BB)	0.441	63.24*	High Importance / Moderate Performance → Priority Zone
Perceived Behavioral Control (PBC)	0.199	71.02	Moderate Importance / High Performance → Sustain
Attitude (AT)	0.159	63.78	Moderate Importance / Moderate Performance → Improve
Subjective Norms (SN)	0.088	73.88	Low Importance / High Performance → Low Priority

Note. *Importance = total effect (direct + indirect) on Investment Intention. Performance = rescaled mean of construct indicators on 0–100 scale: [(mean − minimum) / (maximum − minimum)] × 100. *BB performance (63.24) represents the average across seven sub-construct latent variable scores. Sample averages: importance = 0.222 (construct level); performance = 65.86.*

4.4 IPMA -Indicator Level

Table 4 presents item- and sub-construct-level IPMA results, enabling finer-grained prioritization within the Behavioral Biases construct. Three sub-constructs emerge as belonging to the critical action zone ,above-average importance and below-average performance. Overconfidence holds the highest importance of all sub-constructs in the model (0.209), at a performance of 66.03, which marginally exceeds the sample average (65.86) but remains clustered near it, confirming its status as the most structurally influential bias. Loss Aversion is the most urgent single target: it ranks second in importance (0.175) and records the lowest performance of any construct or indicator in the entire model (55.46), placing it almost 10 percentage points below the sample average ,a gap that represents substantial room for improvement relative to its structural weight. Regret Aversion (importance = 0.130, performance = 58.17) and Anchoring (importance = 0.091, performance = 56.61) constitute a secondary priority cluster, both operating well below average performance despite their meaningful structural importance.

Mental Accounting (importance = 0.160, performance = 65.05) occupies a borderline position near the intersection of the two axes. Availability Bias (0.076, 62.28) and Representativeness (0.096, 64.18) show broadly balanced profiles, warranting maintenance rather than prioritized remediation. Among TPB indicators, PBC items cluster in the above-average performance zone (70.67–71.43) with moderate importance (0.068–0.070), confirming the 'sustain' classification. SN indicators record the highest performance values in the model (73.35–74.79) alongside the lowest importance scores (0.032–0.036), placing them unambiguously in the low-priority quadrant. Figure 1 plots all 16 indicators on the IPMA map, with dashed reference lines at the sample means for importance and performance.

Table 4: Indicator- and Sub-construct-Level IPMA Results -Target: Investment Intention

Indicator / Sub-construct	Importance (Total Effect)	Performance (0–100)
AT1 – Attitude	0.065	64.42
AT2 – Attitude	0.068	64.29
AT3 – Attitude	0.064	62.64
BB: Anchoring (AN)	0.091	56.61
BB: Availability Bias (AV)	0.076	62.28
BB: Loss Aversion (LA) ▲	0.175	55.46
BB: Mental Accounting (MA)	0.160	65.05
BB: Overconfidence (OC) ▲	0.209	66.03
BB: Regret Aversion (RA) ▲	0.130	58.17
BB: Representativeness (RP)	0.096	64.18
PBC1 – Perceived Behavioral Control	0.068	71.43
PBC2 – Perceived Behavioral Control	0.070	70.95
PBC3 – Perceived Behavioral Control	0.069	70.67
SN1 – Subjective Norms	0.032	73.35
SN2 – Subjective Norms	0.036	74.79
SN3 – Subjective Norms	0.032	73.49
Average	**0.090**	**65.86**

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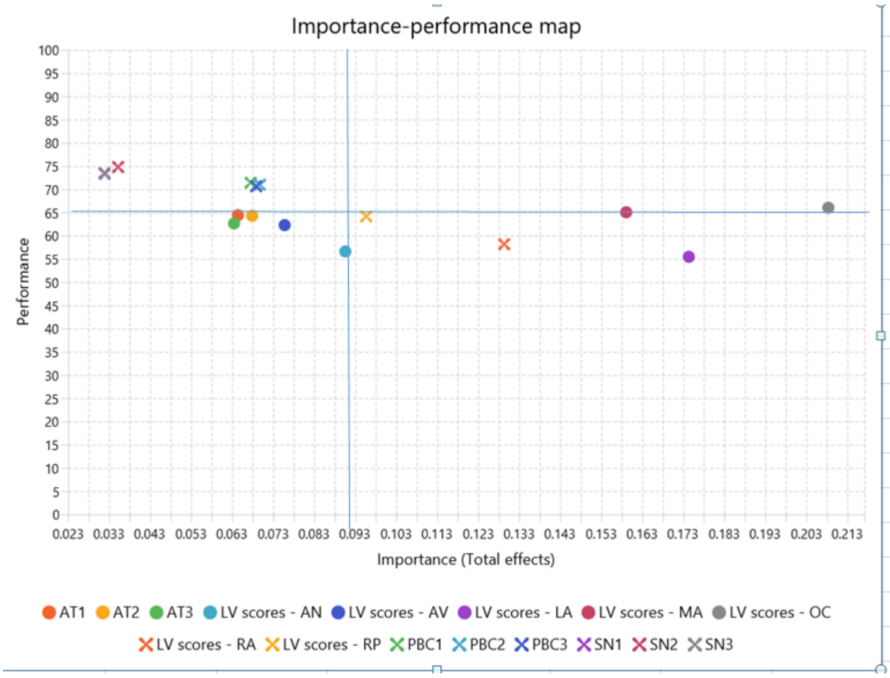
Note. *▲ denotes indicators falling in the critical action zone (above-average importance, below-average performance). BB sub-constructs are represented by latent variable (LV) scores from the first-order constructs. Importance = total effect on Investment Intention; Performance = rescaled mean on 0–100 scale. Average importance = 0.090; average performance = 65.86 (sample-level benchmarks).*

Figure 1: Importance-Performance Map -Investment Intention as Target Construct.



Source. SmartPLS 4.0 IPMA output.

5. DISCUSSION

5.1 Overconfidence as the Highest-Impact Bias

The IPMA findings confirm that overconfidence is not merely the most frequently studied bias in behavioral finance (Barber & Odean, 2001; Glaser & Weber, 2007) but also the most structurally consequential one for investment intention in this sample. With a total effect of 0.209, overconfidence exerts greater structural influence on investment intention than any other individual predictor, including subjective norms (0.088) and the attitude items (0.064–0.068). Its performance level of 66.03 ,closely approximating the sample average ,indicates that overconfidence is both widespread and amenable to intervention. Practitioners who deploy calibration training, scenario-based feedback that highlights past forecast errors, and systematic accuracy scoring can realistically move investors down the overconfidence scale (Merkle, 2017; Pikulina et al., 2017). Fintech platforms that provide traders with personalized accuracy histories and benchmark their return expectations against market indices represent promising channels for scalable overconfidence mitigation (Bhattacharya et al., 2022; Pelster & Gonzalez, 2021).

5.2 Loss Aversion as the Most Urgent Intervention Target

Loss Aversion presents a different profile: high structural importance (0.175) combined with the lowest performance score in the model (55.46). This is the archetype of an IPMA action-zone construct ,there is more 'distance to travel' in improving performance, and each unit of improvement translates into meaningful gains in investment intention. The low performance score reflects the well-documented difficulty that loss aversion poses: it is deeply rooted in evolutionary risk sensitivity and reinforced by the emotional salience of losses relative to gains (Kahneman & Tversky, 1979; Tom et al., 2007; Frydman & Rangel, 2014). Effective interventions include long-term portfolio framing that aggregates returns to reduce the frequency of negative feedback (Thaler et al., 1997), mental simulation exercises that normalize paper losses as a feature of market participation, and gain-framing communication strategies that emphasize cumulative wealth appreciation over single-period outcomes. Regulatory initiatives such as SEBI's (2025) investor awareness campaigns should explicitly address loss aversion through behavioral narratives rather than raw statistical information.

5.3 Regret Aversion and Anchoring: The Secondary Priority Cluster

Regret aversion (importance = 0.130, performance = 58.17) and anchoring (importance = 0.091, performance = 56.61) form a secondary action cluster, both materially below the performance mean while maintaining structural relevance. Regret aversion generates a particular intervention challenge because it is reinforced by social comparison: investors who observe peers profiting from positions they avoided experience counterfactual regret that persists across market cycles (Zeelenberg & Pieters, 2007; Kaur & Kaushik, 2023). Structured investment review processes that separate the quality of a decision from its outcome can reduce regret-driven distortions (Pompian, 2012). Anchoring responds well to interventions that deliberately introduce multiple reference points ,for example, presenting prospective investments alongside both a 52-week low and a forward earnings multiple rather than the purchase price alone (Jain et al., 2023; Furnham & Boo, 2011). Digital platforms can automate this by surfacing contextually relevant anchors within the investment decision interface.

5.4 Perceived Behavioral Control: Sustain, Do Not Over-Invest

Perceived Behavioral Control (importance = 0.199, performance ≈ 71.02) sits in the sustain quadrant. It is the second most structurally important predictor in the model, confirming the established role of financial self-efficacy in driving investment intention (Lusardi & Mitchell, 2014; Arora & Kumari, 2024; Eshpulatov, 2025). However, its high performance indicates that Delhi-NCR retail investors already possess a relatively strong sense of control over their investment behavior, likely a product of rising financial literacy, mobile-platform accessibility, and government-sponsored investor education. The IPMA implication is one of proportionality: while sustaining and marginally improving PBC is worthwhile, committing disproportionate intervention resources to further self-efficacy building ,at the expense of debiasing overconfidence and loss aversion ,would represent a misallocation of effort. Investors who are highly confident in their ability to invest but whose decisions are simultaneously distorted by loss aversion and overconfidence may be more dangerous to themselves than investors with moderate self-efficacy and lower bias levels.

5.5 Attitude: A Mechanism Worth Optimizing

Attitude toward investing (importance = 0.159, performance ≈ 63.78) occupies the moderate zone ,structurally meaningful, performing near but slightly below the sample average. Importantly, attitude also partially mediates the BB–Investment Intention path (indirect effect $\beta = 0.149$, $p < .001$), confirming that behavioral biases shape investment intentions not only directly but also by systematically distorting how investors evaluate the desirability of investing. Interventions that successfully reduce overconfidence and loss aversion will therefore improve attitude formation as a downstream effect, generating a compounding benefit. This mediation finding aligns with recent work by Gautam et al. (2024) and Mehrotra and Srivastava (2025), and reinforces the view that attitude is a pathway to be improved through upstream bias reduction rather than a standalone communication target.

5.6 Subjective Norms: Low Priority, Not Irrelevant

The structural non-significance and high performance of Subjective Norms ($\beta = 0.088$, $p = .113$; performance = 73.88) place it in the low-priority quadrant. This pattern is consistent with findings from other emerging-market investment intention studies where social normative influence plays a secondary role relative to internal psychological drivers (Agustin et al., 2023; Tran et al., 2025). It is possible that the post-pandemic growth of self-directed trading platforms in India has reduced investors' dependence on peer advice, replacing it with app-mediated information and algorithm-driven signals (Bhattacharya et al., 2022). While subjective norms should not be entirely dismissed ,they may matter more for first-time investors or in specific investment categories such as socially responsible funds ,they do not warrant priority attention in the current policy and design environment.

6. CONCLUSION

This study makes three principal contributions. First, it is among the first to apply IPMA within a behavioral finance framework focused on retail investor decision-making, generating an empirically grounded priority ranking of cognitive biases and TPB antecedents rather than merely establishing their statistical significance. Second, it advances the operationalization of behavioral biases as a second-order PLS-SEM construct, demonstrating that this approach provides sufficient sub-dimensional granularity for meaningful IPMA decomposition. Third, it offers practical, resource-allocation-oriented guidance for the emerging field of investor debiasing, identifying overconfidence and loss aversion as the two highest-priority intervention targets for retail investors in India's rapidly evolving capital markets.

Several limitations warrant acknowledgment. The cross-sectional design precludes causal inference and prevents observation of how bias-intention profiles evolve across market cycles. The geographic focus on Delhi-NCR limits generalizability to rural investor populations and to other emerging markets, though the urban, educated, digitally engaged profile of the sample is increasingly representative of India's expanding active-investor base. Self-reported bias scores are subject to social desirability and introspective accuracy limitations inherent to survey methodologies (Amusa & Hossana, 2024). Future research should replicate this IPMA framework using longitudinal data and objective brokerage records, extend it to investor segments stratified by experience level and risk appetite, and test whether IPMA-derived priorities shift during bear-market conditions, when loss aversion and regret aversion effects are likely amplified.

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