“Risk perception, gain-loss evaluation, and digital investment participation: The mediating role of loss aversion in India”

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RISK PERCEPTION, GAIN-LOSS EVALUATION, AND DIGITAL INVESTMENT PARTICIPATION: THE MEDIATING ROLE OF LOSS AVERSION IN INDIA

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Abstract

This study aims to examine how risk perception, perceived gain, and perceived loss influence digital investment participation intention, with loss aversion as a mediating mechanism in the context of India. Structural equation modeling was applied to survey responses from 418 digitally active investors in India, collected online between January 15, 2025 and July 12, 2025, using judgmental sampling to ensure respondents possessed prior investment exposure and were actively engaged in digital investment environments, thereby enhancing the contextual relevance of the sample. The model explains 62.4% of the variance in investment participation intention and 58.7% in loss aversion. Perceived gain positively influences intention ($\beta = 0.279$, $p < 0.001$), while perceived loss negatively affects it ($\beta = -0.226$, $p < 0.001$). Risk perception has no direct effect ($\beta = -0.061$, $p = 0.226$) but increases loss aversion ($\beta = 0.111$, $p = 0.010$). Loss aversion positively predicts intention ($\beta = 0.564$, $p < 0.001$). Mediation analysis confirms significant indirect effects for all predictors. The findings suggest that, within this young and digitally active Indian sample, investment intention is shaped by perceived gains, perceived losses, and loss aversion as an affective mediating mechanism in digital investment environments.

Keywords investment, behavior, loss, aversion, risk, perception, prospect, digital, finance

JEL Classification G41, G11, D81

INTRODUCTION

The proliferation of digital investment platforms has fundamentally altered how individuals engage with financial markets, particularly in emerging economies. The widespread adoption of mobile trading applications, peer-based investment communities, and real-time price visibility has significantly reduced traditional barriers to entry and expanded retail investor participation (Zéman et al., 2024). As a result, individual investors are increasingly exposed to environments characterized by high uncertainty and volatility, where financial decisions must often be made under time constraints and limited information.

India's digital investment relevance is reflected in the rapid expansion of its investor base; the National Stock Exchange of India reported that India crossed 11 crore unique registered investors and over 21 crore total investor accounts in January 2025 (National Stock Exchange of India, 2025). This shift is especially visible among younger investors who access financial markets through real-time digital information and peer-based discussions. Therefore, understanding how this segment evaluates risk, potential gain, potential loss, and loss sensitivity is important for explaining participation intention in an emerging digital finance market.

In such settings, investment decisions are no longer driven solely by objective evaluations of risk and return but are increasingly influenced by subjective interpretations of potential gains, losses, and uncertainty. The growing complexity of digitally mediated financial environments amplifies these effects, as continuous information flows and social comparison mechanisms intensify individual responses to market signals.

Despite this shift, a central scientific problem remains insufficiently addressed. Existing research tends to examine key psychological factors influencing investment behavior in isolation or focuses primarily on their direct relationships with decision outcomes. Such approaches provide limited insight into how these factors interact to shape actual participation behavior under conditions of uncertainty.

More importantly, the behavioral mechanism through which individual perceptions of gains, losses, and risk are translated into investment participation remains unclear. In emerging digital market contexts, where rapid feedback loops and visible social outcomes are prevalent, this gap becomes particularly critical. This lack of an integrated understanding of how cognitive evaluations and emotional processes jointly shape participation under uncertainty constitutes the central problem addressed in this study.

1. LITERATURE REVIEW

Conventional financial models rest on the assumption that investors make resource allocation decisions through dispassionate assessments of risk and expected return. Yet an extensive body of behavioral finance research has established that investment behavior is far from rational, being systematically distorted by cognitive biases and affective responses (Hirshleifer, 2015; Sattar et al., 2020). Evidence indicates that risk perception exerts a notable influence on investors' willingness to enter financial markets (Holzmeister et al., 2020; Saivasan & Lokhande, 2022), while an individual's prior market experience conditions how new financial opportunities are interpreted (Zhou, 2023). Furthermore, anticipated gains and losses occupy a central role in shaping participation decisions, most acutely under conditions of uncertainty or high volatility (Singh et al., 2024). These variables seldom function in isolation; rather, they are filtered through psychological framing processes that ultimately determine how potential outcomes are construed and translated into action.

A growing strand of behavioral finance research underscores that investors do not process gains and losses symmetrically. The concept of loss aversion, which denotes the disproportionately greater psychological weight assigned to potential losses relative to gains of equal magnitude, has emerged as a central construct for understanding why investor behavior systematically deviates from purely rational choice models (Sokol-Hessner & Rutledge, 2019). Documented consequences include a reduced willingness to enter positions. Real-world evidence further indicates that loss aversion significantly diminishes investors' risk-taking propensity and discourages portfolio diversification, thereby shaping their investment decision-making behavior. It is also associated with prolonged indecision and premature exit from investments when losses loom, whereas anticipated gains tend to attract engagement, albeit with heightened vigilance. Despite this evidence, prior research has largely treated gain perception, loss perception, and risk perception as independent behavioral predictors, neglecting the possibility that these perceptions may converge through a shared affective pathway (Sathya & Gayathiri, 2024).

Prospect Theory provides a rigorous conceptual framework for understanding these behavioral asymmetries. It explains such asymmetries by proposing that individuals evaluate outcomes relative to internal reference points and assign greater psychological weight to losses than to equivalent gains (Kahneman & Tversky, 1979). This framework offers a robust basis for examining how perceptions of gains, losses, and risk influence investment behavior under conditions of uncertainty. Applied research further demonstrates that Prospect Theory effectively explains how individuals actually make decisions in situations where outcomes are uncertain, particularly when choices are shaped by personal reference points (De Moraes Ramos et al., 2011).

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In digitally networked markets, these behavioral tendencies are further amplified by continuous information flows, social comparison, and real-time feedback. The influence is further strengthened by social comparison, which also leads to an increase in fear of missing out and ultimately results in stronger emotionally driven responses in digital environments (Cahyani & Pangestuti, 2023), which dynamically shape investor perceptions and responses (Hong et al., 2023). Such conditions can intensify how individuals interpret potential gains, losses, and risks, thereby influencing their investment behavior under uncertainty.

A growing body of empirical work corroborates these mechanisms. Neuroscientific findings show that anticipating a loss elicits stronger neural activation than anticipating an equivalent gain (Chen et al., 2022), which is consistent with the asymmetry posited by Prospect Theory. Within emerging market settings, cognitive biases such as herding, overconfidence, and fear of missing out may compound heightened loss sensitivity and amplify emotionally driven investment responses (Gurung et al., 2024). Research on digital and online investment platforms further demonstrates that elevated perceived risk does not automatically discourage participation; behavioral outcomes are instead governed largely by how those risks are emotionally framed (Wendy, 2024). Taken together, the evidence points to the conclusion that participation decisions in contemporary investment settings are driven not by dispassionate risk evaluation alone, but by the emotional lens through which uncertain outcomes are interpreted.

The mechanisms embedded in Prospect Theory are further amplified in digitally enabled financial environments, where uninterrupted information streams, visible peer activity, and algorithm-driven signals continuously recalibrate investor reference points and emotional states. Contextual empirical work substantiates this amplification effect. Studies of social trading platforms, for instance, document the significant role of peer-based signals and fear of missing out (FOMO) in shaping whether individuals choose to participate (Gupta & Shrivastava, 2022). Additionally, younger investors who constitute a disproportionately large share of digital market participants show greater vulnerability to overconfidence and emotionally reactive trading patterns. Meanwhile, evidence on risk perception remains inconclusive: some studies find that higher perceived risk suppresses investment intent, while others demonstrate that digitally experienced investors may reframe or tolerate such risk when sufficiently compelling opportunity cues or social endorsement are present. Investment intention, broadly considered a dependable antecedent of actual market behavior, captures an individual's psychological preparedness to commit capital. Prior studies have extensively examined its antecedents, including trust, financial literacy, institutional credibility, and demographic factors (Semeru & Negoro, 2024; Shiva et al., 2022). Yet the affective channel through which perceptions of potential outcomes translate into participation decisions remains inadequately theorized within any single unified model. Notably, scant research has examined how perceived gains, perceived losses, and risk perception operate concurrently through the mechanism of loss aversion to determine participation intention in emerging digital investment contexts.

Furthermore, prior investment experience has generated inconsistent empirical findings. In light of its documented role in financial decision-making, past investment experience was incorporated into the model as a control variable to capture systematic baseline variation in investment intentions among respondents. Some scholars find that accumulated experience bolsters investor confidence and attenuates emotional bias, while others contend that experience can entrench heuristic-driven decision patterns rather than resolve them (Sattar et al., 2020). This tension implies that prior exposure may not straightforwardly translate into intention; its effect may instead be contingent on the emotional lens through which past outcomes are reinterpreted.

Synthesizing the evidence, cognitive appraisals, emotional biases, and contextual factors jointly influence investment behavior. However, prior research has largely examined these elements in isolation, offering limited insight into how they interact within a unified behavioral framework. This limitation is particularly evident in emerging digital investment contexts, where rapid information flows and social influences intensify decision-making complexity.

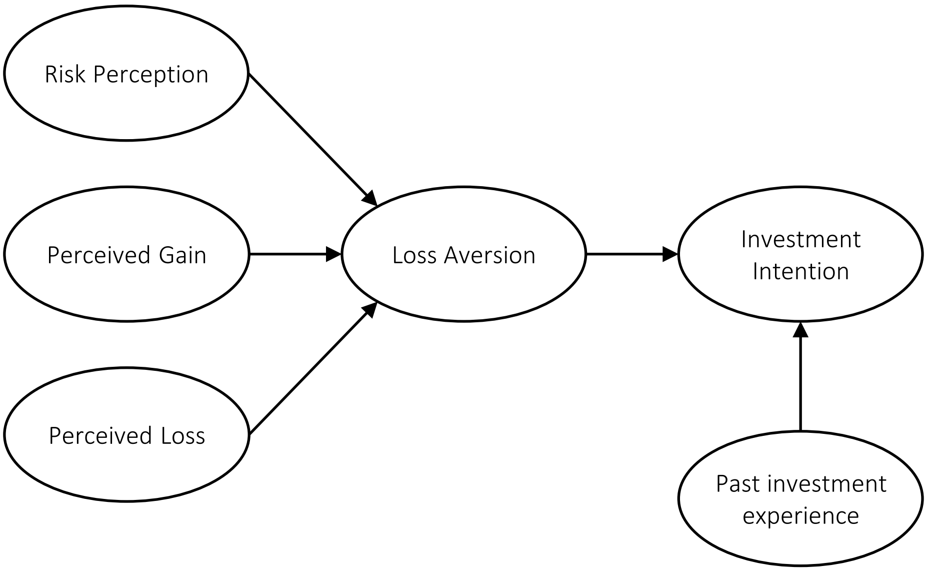

Figure 1. Research model

Furthermore, existing research provides limited understanding of how these cognitive and emotional factors jointly translate into investment participation intention under conditions of uncertainty. This gap highlights the need for a more integrated perspective linking perception, emotional processing, and behavioral intention.

Although classical Prospect Theory generally associates loss aversion with greater sensitivity to losses and reduced risk-taking, digital investment environments may alter how loss sensitivity translates into behavioral intention. In such environments, investors are continuously exposed to price movements, peer activity, benchmark comparisons, and opportunity cues. As a result, nonparticipation may itself be perceived as a potential loss, particularly when investors fear missing profitable opportunities or falling behind comparable others. Hence, loss-sensitive investors may not necessarily withdraw from digital investment environments; instead, they may remain engaged through cautious monitoring, planning, and selective participation. In this study, loss aversion is interpreted as a loss-sensitive investment orientation that may encourage controlled participation rather than impulsive risk-taking.

Therefore, this study aims to examine how risk perception, perceived gain, and perceived loss influence digital investment participation intention among young and digitally active investors in India, with loss aversion as a mediating mechanism.

H1a: Risk perception negatively influences investment intention.

H1b: Risk perception positively influences loss aversion.

H1c: Loss aversion mediates the relationship between risk perception and investment intention.

H2a: Perceived gain positively influences investment intention.

H2b: Perceived gain positively influences loss aversion.

H2c: Loss aversion mediates the relationship between perceived gain and investment intention.

H3a: Perceived loss negatively influences investment intention.

H3b: Perceived loss positively influences loss aversion.

H3c: Loss aversion mediates the relationship between perceived loss and investment intention.

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H4: Loss aversion positively influences investment intention.

The proposed research model is illustrated in Figure 1.

2. METHOD

The research design was executed in three sequential stages:

1) development of the measurement instrument and operationalization of constructs drawing on validated scales;

2) primary data collection from qualified individual investors across India; and

3) structural model estimation and hypothesis evaluation through Partial Least Squares Structural Equation Modeling (PLS-SEM).

The conceptual framework under investigation addresses how psychological and behavioral determinants, specifically risk perception, perceived gain, perceived loss, loss aversion, and prior investment experience, jointly shape investment intention. PLS-SEM was selected due to its suitability for analyzing complex research frameworks involving multiple latent variables and its robust performance with moderately sized samples. It is particularly effective in handling structural complexity and supporting prediction-oriented research (Hair & Alamer, 2022), making it an appropriate methodological choice for this study.

Table 1. Measurement items table

Construct	Source	Sample item
Investment intention	Ajzen (1991)	I intend to put at least half of my investment money into the stock market. I intend to engage in portfolio management activities at least twice per week I intend to perform my own investment research instead of using outside advice. I intend to compare my portfolio performance to that of professional managers.
Loss Aversion	Awais et al. (2016)	I usually overweight the losses in my investments. I can easily take investment decisions only during market stability. I like to clearly know about my target before the implementation of my plan It is very difficult for me to easily take investment decisions during high levels of price fluctuations in the market. I may not randomly pick any stock during insecure conditions of the market. I always try to measure my returns with specific benchmarks I like to set or know about the point of attraction for my investment. I don't want to take an action on the basis of an expert's actions. Before taking any action, I like to observe the movements of my friends or peers to reduce the chance of risk. I don't want to take any risk in case of a financially unsound position. I always need guaranteed payments from my investments. I may reduce my decision-making ability during stress. I may not easily make decisions regarding those stocks which I have not traded earlier. I can generate profits on the basis of my own decisions.
Past Experience	Zhou (2023)	I would invest in companies that I know. My Intuition has a major role in my investment choices. Will look at past performance before investing. I believe past trends would continue in the future. I invest where I feel I will do well. I reflect on past financial decisions when making current decisions.
Perceived Loss	Shiva et al. (2022)	I worry that investing in this option could lead to a financial loss. When I think about this investment, the possibility of losing money feels high. I feel uneasy about the risk of losing part of my capital if I invest.
Perceived Gain	Singh et al. (2024)	This investment could enhance my financial standing and future security. This investment would improve my confidence in achieving my financial goals. This investment would make me feel more financially empowered and successful.
Risk Perception	Weber et al. (2002)	Investing 5% of your annual income in a very speculative stock. Investing 5% of your annual income in a conservative stock. Investing 10% of your annual income in government bonds (treasury bills). Investing 10% of your annual income in a moderate growth mutual fund.

All constructs were operationalized using items drawn from validated, peer-reviewed scales (see Table 1). Responses were recorded on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), except for Risk Perception, which used DOSPERT perceived-risk anchors ranging from 1 (Not at all risky) to 5 (Extremely risky).

Consistent with Prospect Theory, the model includes risk perception, perceived gain, perceived loss, loss aversion, investment intention, and past investment experience. Measurement items were adapted from established scales in behavioral finance to ensure reliability and comparability, with minor modifications to suit the context of digital investment environments.

Loss aversion was measured following Awais et al. (2016). Given the breadth of the adopted items, the construct is interpreted in this study as a broader loss-sensitive investment orientation rather than a pure experimental measure of loss aversion. Perceived loss captured anticipated downside loss from investing, while perceived gain reflected expected returns (adapted from Cresswell, 2004). Risk perception was assessed using DOSPERT-based items (Weber et al., 2002), and investment intention followed TPB-based measures (Ajzen, 1991), conceptualized in this study as the individual's intention to actively participate in digital investment activities. Past investment experience reflected prior exposure to financial products (e.g., Zhou, 2023).

The selection of constructs and items reflects their relevance to explaining how cognitive evaluations of gains, losses, and risk translate into investment intention through loss aversion in digitally mediated settings. Construct quality was assessed using standard indicators, including factor loadings, composite reliability (CR), AVE, HTMT, SRMR, and VIF (Li & Lay, 2024). The complete questionnaire, including all measurement items, scale adaptations, and survey instrument details, is provided in a publicly accessible Zenodo repository to ensure transparency and replicability of the study.

The sample data were drawn from individual investors in India, a country representing one of the world's fastest-expanding digital investment markets. India was selected as the research context due to its rapidly growing fintech ecosystem and increasing participation of retail investors in digital investment platforms. To secure respondents possessing at least a foundational level of financial awareness, judgmental sampling was employed. Eligibility required satisfying at least one of two conditions:

(i) hands-on experience with financial products in the preceding two years; or

(ii) active participation in digital investment platforms or investment-oriented communities.

This sampling strategy deliberately targeted "informed respondents" whose views were rooted in genuine or aspirational engagement with financial decision-making contexts, thereby enhancing the relevance and reliability of the data collected. The final sample of 418 respondents clears the minimum threshold recommended for PLS-SEM and is adequate to accommodate the model's structural complexity.

Respondents were sourced via online investment-focused communities and relevant professional networks. Data were collected between January 15, 2025 and July 12, 2025 through an online survey administered across India, ensuring access to digitally active participants aligned with the study's focus and allowing sufficient time to capture responses from actively engaged digital investors. The data used in this study were collected specifically for this research and have not been used in any prior publication. Ethical considerations were carefully addressed throughout the study. Participation was voluntary, and informed consent was obtained from all respondents prior to data collection. The survey was conducted anonymously, and no personally identifiable information was collected, ensuring respondent confidentiality. As the study involved non-sensitive, anonymous survey data and did not include vulnerable populations, formal ethics committee approval was not required. The study adhered to standard ethical guidelines for social science research.

Of the 1,000 survey invitations distributed, 418 completed responses were received, representing a response rate of 41.8%. The resulting sample is predominantly young, digitally engaged, and finan-

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cially informed: 73% male, 27% female, 69% aged under 30, with 49% students and 48% employed professionals. The demographic profile of respondents is presented in Table 2. Although the sample does not mirror the full diversity of Indian investors, it captures the youth-driven, technology-oriented cohort at the forefront of digital finance adoption. This scope constrains generalization but offers valuable insight into the demographic segment most actively shaping digital investment behavior in emerging markets.

Table 2. Demographic profile of investors (n = 418)

Variables	Category	Frequency	Percentage
Gender	Male	304	73%
	Female	114	27%
Age	18-24 Years	124	30%
	25-30 Years	161	39%
	31-39 Years	90	22%
	40-50 Years	36	9%
	Above 50 Years	7	2%
Education	High School	89	21%
	Bachelor's Degree	202	48%
	Master's Degree	109	26%
	Other	18	4%
Occupation	Student	203	49%
	Working	200	48%
	Retired	15	3%
Annual Income	Less than ₹5 lakhs	275	66%
	₹5-8 lakhs	65	16%
	₹8-10 lakhs	52	12%
	More than ₹10 lakhs	26	6%

All hypotheses were tested using PLS-SEM as operationalized in SmartPLS. This technique is well-suited to models involving multiple latent constructs and moderate sample sizes, and it aligns naturally with the objective of applying Prospect Theory to contemporary digital investment settings. Data analysis unfolded across two consecutive stages.

In the first stage, attention was directed toward validating the measurement model by verifying the reliability and validity of each construct. Internal consistency was gauged through Cronbach's alpha alongside composite reliability (CR), as relying on a single reliability measure may be insufficient (Cheung et al., 2024). However, recent methodological research also warns against placing too much trust in common rule-of-thumb cutoffs for Cronbach's alpha, indicating that reported reliability values may sometimes be influenced by measurement flexibility or selective reporting practices (Hussey et al., 2023).

Convergent validity was verified via average variance extracted (AVE), while discriminant validity was established through the heterotrait-monotrait (HTMT) ratio, which is considered a more stringent criterion for assessing discriminant validity (Ab Hamid et al., 2017). For indicator screening, adapted scales required $\lambda \geq .50$ (with .60 preferred). Items falling below .50 were excluded, while those in the .50-.59 range were retained only when supported by content validity and satisfactory CR/AVE/HTMT values.

On this basis, II4 ($\lambda = .544$) was retained because it captures a distinct intention facet (near-term action commitment) absent from the other items. Inner VIF values were inspected to evaluate multicollinearity. Common method bias (CMB) was further examined using both procedural and statistical strategies, including the full collinearity VIF test.

The second stage entailed evaluation of the structural relationships by computing standardized path coefficients (β) and testing their significance via a bootstrapping routine using 5,000 resamples with bias-corrected two-tailed confidence intervals. Explanatory power was quantified using R^2 statistics, while out-of-sample predictive relevance was assessed through Q^2 (blindfolding) in conjunction with PLS-Predict. Effect magnitudes were gauged using f^2 statistics. Global model fit was evaluated via the standardized root mean square residual (SRMR), with values under 0.08 conventionally signifying adequate fit. Throughout this study, β refers to standardized path coefficients, λ to standardized factor loadings, CR to composite reliability, and AVE to average variance extracted. Q^2 reflects predictive relevance, and f^2 represents effect size. The goodness-of-fit (GoF) index is included for completeness, though the principal criteria are SRMR, CR, AVE, HTMT, and PLS-Predict diagnostics. As a sensitivity check, re-running the model without II4 produced negligible changes in CR and AVE and no alterations in the direction or significance of structural paths.

3. RESULTS

This section reports the sample characteristics, measurement model assessment, and results of the structural model analysis. A total of 418 respondents, gathered through digital platforms, constituted the study sample. The demographic characteristics of the respondents are summarized in Table 2. The sample is predominantly young and digitally engaged, with 73% male and 27% female participants. The majority fall within the 18-30 age group and possess at least a bachelor's degree. Students (49%) and working professionals (48%) together represent the most active segment of digital investors in India. While this composition limits broad generalizability, it provides focused insight into the cohort driving digital investment participation.

Measurement model's psychometric properties were assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Table 3 presents the evaluation indicators. All Variance Inflation Factor (VIF) values were below 5, indicating no multicollinearity concerns. Cronbach's alpha values ranged from 0.664 to 0.816, exceeding the acceptable threshold of 0.60. Composite reliability values ranged from 0.798 to 0.930, surpass-

Table 3. Measurement model assessment: loadings, reliability, and convergent validity

Construct	Item	SL	CR	α	AVE
Construct 1: Investment Intention	II1	0.725	0.798	0.664	0.502
	II2	0.823			
	II3	0.712			
	II4	0.544			
Construct 2: Loss Aversion	LA1	0.596	0.93	0.919	0.508
	LA2	0.688			
	LA3	0.773			
	LA4	0.691			
	LA5	0.741			
	LA6	0.747			
	LA7	0.773			
	LA9	0.679			
	LA10	0.681			
	LA11	0.777			
	LA12	0.663			
	LA13	0.71			
	LA14	0.723			
Construct 3: Past Investment Experience	PE1	0.663	0.867	0.816	0.523
	PE2	0.738			
	PE3	0.631			
	PE4	0.757			
	PE5	0.734			
	PE6	0.804			
Construct 4: Perceived Gain	PG1	0.814	0.878	0.791	0.706
	PG2	0.89			
	PG3	0.814			
Construct 5: Perceived Loss	PL1	0.811	0.841	0.719	0.639
	PL2	0.803			
	PL3	0.783			
Construct 6: Risk Perception	RP2	0.833	0.868	0.773	0.687
	RP3	0.832			
	RP4	0.821			

Notes: SL = standardized loading; CR = composite reliability; α = Cronbach's alpha; AVE = average variance extracted

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ing the recommended threshold of 0.70. Average Variance Extracted (AVE) values exceeded 0.50 for all constructs, confirming convergent validity.

Factor loading (λ) ≥ .50 acceptable for adapted scales (.60 preferred); II4 (λ = .544) retained for content validity. Removing II4 produced no meaningful change in CR, AVE, or path significance.

Factor loadings ranged from 0.544 to 0.881. Item II4 (λ = 0.544) was retained due to its theoretical relevance, while all other items exceeded the preferred threshold of 0.60. All constructs satisfied the criteria of CR ≥ 0.70, AVE ≥ 0.50, and HTMT < 0.85. A sensitivity analysis excluding II4 yielded no meaningful changes in reliability or structural relationships. These results confirm the reliability and validity of all constructs.

Discriminant validity was assessed using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. As shown in Table 4, the square root of AVE for each construct exceeded its correlations with other constructs, satisfying the Fornell-Larcker criterion. All HTMT values were below the threshold of 0.85, providing additional support for discriminant validity. These findings confirm that all constructs are empirically distinct.

Discriminant validity is established when diagonal values are higher than all values in their row and column.

The structural model was evaluated using R^2, Q^2, and model fit indicators. Table 5 shows that all Q^2 values exceeded zero, indicating predictive relevance. The model explains 62.4% of the variance in Investment Intention and 58.7% in Loss Aversion. Model fit indices were within acceptable limits (SRMR < 0.08). PLS-Predict analysis indicated that the model demonstrates satisfactory predictive performance compared to linear regression benchmarks. Common method bias was assessed using full collinearity VIF, with all values below 3.3, indicating no significant bias. Figure 2 presents the standardized path coefficients, and Table 6 summarizes the hypothesis testing results.

Table 5. Structural model fit indices

Construct	R^2	Q^2
Investment Intention	0.624	0.246
Loss Aversion	0.587	0.214

Notes: Q^2 = cross-validated redundancy; R^2 = coefficient of determination.

The results indicate that loss aversion has a significant positive effect on investment intention (β = 0.564; t = 8.91; p < 0.001). Perceived gain significantly influences investment intention (β = 0.279; t = 5.84; p < 0.001), while perceived loss has a significant negative effect (β = −0.226; t = 4.94; p < 0.001). Risk perception (β = −0.061; t = 1.21; p = 0.226) and past investment experience (β = 0.045; t = 0.67; p = 0.506) do not have significant direct effects. Among the predictors of loss aversion, perceived gain (β = 0.398; t = 6.37; p < 0.001), perceived loss (β = 0.234; t = 3.66; p < 0.001), and risk perception (β = 0.111; t = 2.57; p = 0.010) all have significant positive effects.

Loss aversion significantly mediates the relationships between risk perception (indirect β = 0.063; t = 2.49; p = 0.013), perceived gain (indirect β = 0.225; t = 5.31; p < 0.001), and perceived loss (indirect β = 0.132; t = 3.92; p < 0.001) and investment intention. For perceived loss, the direct effect is negative while the indirect effect via loss aversion is positive, indicating competitive mediation. Total effects (Table 6) show that perceived gain is the strongest predictor of investment intention, followed by perceived loss and risk perception.

Table 4. Discriminant validity (Fornell-Larcker criterion)

Construct	II	LA	PIE	PG	PL	RP
Investment Intention (II)	0.708					
Loss Aversion (LA)	0.462	0.713				
Past Investment Experience (PIE)	0.388	0.446	0.723			
Perceived Gain (PG)	0.515	0.478	0.391	0.840		
Perceived Loss (PL)	0.429	0.498	0.412	0.455	0.799	
Risk Perception (RP)	0.398	0.522	0.437	0.414	0.495	0.829

Note: Bold values on the diagonal represent the square roots of AVE. Off-diagonal values are the inter-construct correlations.

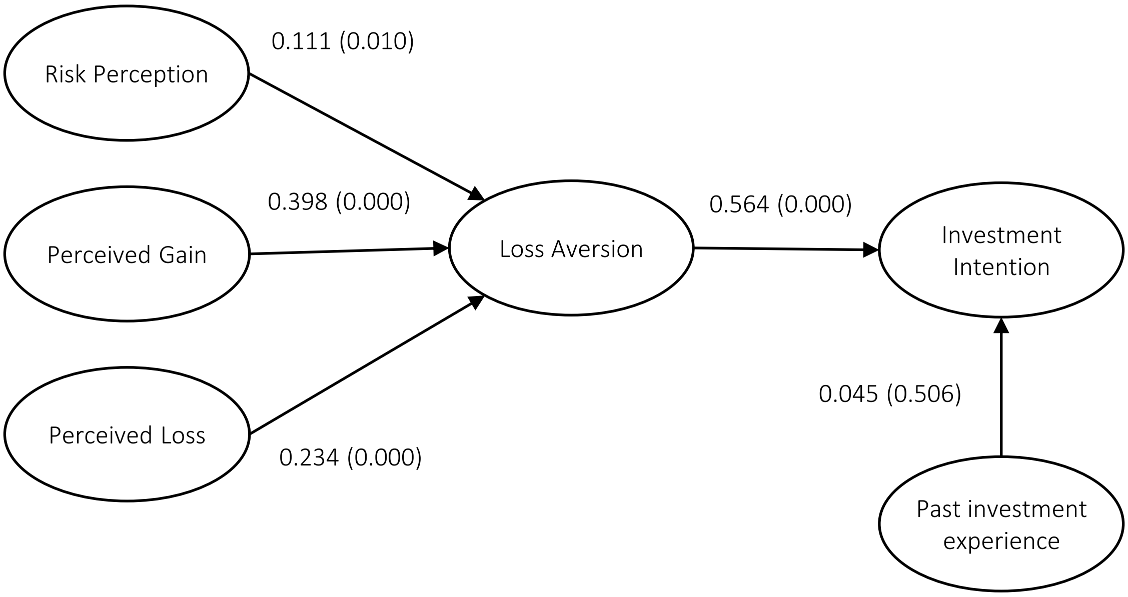

Figure 2. Structural model results: standardized path coefficients and significance

Table 6. Hypothesis testing results: direct, indirect, and total effects (bootstrapped)

Hypothesis	Relationship	Result
H1a	Risk Perception → Investment Intention	Not Supported
H1b	Risk Perception → Loss Aversion	Supported
H1c	RP → Loss Aversion → Investment Intention	Supported
H2a	Perceived Gain → Investment Intention	Supported
H2b	Perceived Gain → Loss Aversion	Supported
H2c	PG → Loss Aversion → Investment Intention	Supported
H3a	Perceived Loss → Investment Intention	Supported
H3b	Perceived Loss → Loss Aversion	Supported
H3c	PL → Loss Aversion → Investment Intention	Supported
H4	Loss Aversion → Investment Intention	Supported
	Past Experience → Investment Intention	Not Significant

Note: $p < 0.05$ is significant; $p < 0.01$ is highly significant.

The hypothesis testing results indicate that H1b, H1c, H2a, H2b, H2c, H3a, H3b, H3c, and H4 are supported, whereas H1a and the effect of past investment experience are not supported.

4. DISCUSSION

This study examines how investment participation intention is shaped not only by rational risk-return considerations but also by how individuals perceive potential gains and losses and the emotional significance attached to them. Drawing on Prospect Theory, the findings indicate that in digitally mediated investment contexts, behavioral intentions appear to be influenced not only by direct cognitive assessments of risk but also by emotionally mediated evaluations of gains and losses. Among the predominantly young and digitally engaged investors in India, perceived gains and losses significantly influence loss aversion, which in turn plays a central role in shaping participation decisions.

A key finding is that risk perception does not directly affect investment intention. Instead, it operates indirectly by increasing loss aversion. This suggests that recognizing uncertainty alone is insufficient to deter participation; rather, its influence depends on how it is emotionally processed. This result differs from earlier empirical studies, which found that higher risk perception has a sig-

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nificant negative influence on investment decisions (Ainia & Lutfi, 2019). This suggests that in digital settings, perceived risk does not necessarily stop people from participating directly; instead, it influences behavior indirectly through emotional factors, such as fear of loss. This finding supports prior research emphasizing the mediating role of emotional biases in the risk–intention relationship (Shafqat & Malik, 2021) and aligns with evidence that risk perception does not uniformly suppress participation in digital investment contexts (Hong et al., 2023; Wendy, 2024). However, it extends this literature by demonstrating that in digitally interconnected environments, emotional amplification mechanisms may outweigh purely cognitive risk evaluations.

Perceived gain emerges as the strongest direct predictor of investment intention. This finding is consistent with prior studies showing that anticipated gains significantly increase willingness to invest (Qi et al., 2022) and supports Prospect Theory's asymmetric valuation of outcomes. At the same time, it extends existing evidence by revealing that anticipated gains also heighten loss aversion, suggesting that the expectation of returns may simultaneously intensify emotional vigilance. Similarly, gain-framed signals in digital environments appear to both encourage participation and increase sensitivity to potential downside (Dezecache & Mercier, 2017).

The role of loss aversion emerges as an important and theoretically relevant finding of this study, but it requires careful interpretation. Traditional Prospect Theory associates loss aversion with greater sensitivity to losses than equivalent gains, often resulting in withdrawal, risk avoidance, or reduced willingness to enter risky positions (Kahneman & Tversky, 1979). Therefore, the positive effect of loss aversion on investment intention may appear counterintuitive if interpreted as pure classical loss aversion. However, in the present study, the adopted measure captures a broader loss-sensitive investment orientation, including caution under market instability, certainty seeking, benchmark monitoring, peer observation, stress response, and familiarity-based decision-making. From this perspective, the positive association suggests cautious engagement rather than unrestricted risk-taking. This interpretation is consistent with neuroscientific and behavioral evidence showing that anticipated losses generate strong emotional activation and vigilance (Tom et al., 2007; Sokol-Hessner & Rutledge, 2019). In digitally mediated investment environments, where investors are continuously exposed to real-time market movements, peer activity, benchmark comparisons, and opportunity cues, non-participation may itself be perceived as a potential loss. Prior studies also suggest that peer influence, herding tendencies, and fear of missing out can shape investment participation in digital and social trading contexts (Gupta & Shrivastava, 2022; Jose, 2024). Thus, loss-sensitive investors may continue to express investment intention because participation allows them to monitor opportunities, reduce uncertainty, and avoid the regret of missing out. The observed competitive mediation for perceived loss further supports this interpretation: although perceived loss directly reduces investment intention, its indirect effect through loss-sensitive orientation increases intention, indicating that emotional framing can convert perceived downside into cautious but active participation.

Past investment experience does not show a significant direct effect on intention. This finding aligns with prior research suggesting that experience does not necessarily lead to more rational or stable financial behavior (Zhou, 2023). Instead, the results indicate that experience functions as contextual input, while emotional interpretation remains the dominant driver of behavior. In rapidly evolving digital environments, particularly among younger investors, immediacy, social comparison, and behavioral cues may outweigh experiential learning in shaping participation decisions.

Taken together, these findings, they reinforce Prospect Theory's core proposition that individuals evaluate their outcomes relative to reference points and then respond asymmetrically to gains and losses (Kahneman & Tversky, 1979). However, this study extends the theory by demonstrating that, in digitally mediated financial ecosystems, loss aversion acts as the central mechanism linking perception and behavior.

This is consistent with emerging evidence on digital investment environments, where peer influence and fear of missing out significantly shape participation decisions (Jose, 2024). Investment participation thus emerges not solely from rational calculation but from the interaction between cognitive evaluation and emotionally driven responses, consistent with evidence that behavioral biases, such as overconfidence, ultimately lead investors to trade excessively and underperform (Barber & Odean, 2000).

This study contributes to the literature by demonstrating that loss aversion functions not only as a mediating bias but as an active behavioral regulator linking cognitive evaluation to investment participation in digital contexts. From a practical perspective, these findings have important implications. Financial educators and advisors should recognize that loss sensitivity does not necessarily suppress participation and can, when appropriately framed, support informed engagement. Communication strategies that balance downside risks with opportunity costs may help moderate extreme emotional reactions. Digital platforms may benefit from incorporating tools such as scenario simulations, risk visualization dashboards, and structured feedback mechanisms to encourage more reflective decision-making. At the policy level, strengthening financial literacy and transparency in digital finance ecosystems may enable investors to interpret gains and losses more effectively and reduce emotionally driven volatility.

Future research may extend this work by examining longitudinal changes in emotional mediation as investors accumulate experience. Experimental studies manipulating gain-loss framing in digital environments could further clarify causal mechanisms. Expanding the sample to include older, institutional, or less digitally engaged investors would improve generalizability. Additionally, incorporating variables such as overconfidence, macroeconomic uncertainty, or market shocks may provide deeper insight into how cognitive and emotional processes interact across different financial contexts.

CONCLUSIONS

This study examined how risk perception, perceived gain, and perceived loss influence digital investment participation intention among young and digitally active investors in India, with loss aversion acting as a mediating mechanism. The findings indicate that perceived gain and perceived loss exert significant direct effects on investment intention, whereas risk perception does not directly influence participation. Instead, its effect operates indirectly through loss aversion. Notably, loss aversion, operationalized as loss-sensitive investment orientation, emerges as a central factor, not only mediating all key relationships but also exerting a strong positive influence on investment intention.

These findings suggest that, among the sampled young and digitally active investors in India, investment intention in digitally mediated environments is shaped less by objective risk assessment and more by the emotional interpretation of potential outcomes. In particular, loss aversion functions as a behavioral regulator, where sensitivity to potential losses can motivate participation when inaction itself is perceived as a loss. This underscores the role of emotional framing as a key mechanism in financial decision-making in digital markets. From a practical standpoint, the results imply that financial education, advisory practices, and platform design should account for emotional responses alongside cognitive evaluations. Tools that enable investors to interpret gains and losses more reflectively may help reduce reactive decision-making.

A key limitation concerns the operationalization of loss aversion. Although the scale was adapted from prior behavioral finance research, it reflects loss aversion in a broader applied investment setting and may not fully correspond to a narrowly defined experimental Prospect Theory measure. Future research should therefore validate this relationship using more refined experimental, behavioral, or incentive-compatible measures of loss aversion. Longitudinal studies may also examine whether this loss-sensitive orientation changes as investors gain experience, while broader and more diverse samples could improve the generalizability of the findings across different investor groups and contexts.

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DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

The authors declare that no generative AI was used to generate research content, data analysis, or results; AI tools were used solely for language editing purposes.

DATA AVAILABILITY

The dataset, along with the full survey questionnaire, measurement instrument, and supporting materials used in this study, is publicly available on Zenodo at https://doi.org/10.5281/zenodo.19681557, ensuring transparency and facilitating replication.

AUTHOR CONTRIBUTIONS

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Methodology: Mrinal Raj, Faiz Anwar.
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Software: Mrinal Raj.
Supervision: Mamta Singh.
Validation: Manish Kumar.
Visualization: Manish Kumar, Mamta Singh.
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