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The Effect of Overconfidence, Loss Aversion, and Optimism Bias on Investment Decisions among Fintech Investors in Garut Regency

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Abstract

This study examines the effect of overconfidence, loss aversion, and optimism bias on the investment decisions of fintech investors in Garut Regency, West Java. Retail participation in the Indonesian capital market has grown rapidly, led by young people who invest through digital platforms, while the value of assets recorded in the market declined in 2026; this makes psychological biases a practical concern. A quantitative explanatory design was applied. Primary data were collected from 336 investors living in 40 sub-districts using a five-point Likert questionnaire and analysed with multiple linear regression after validity, reliability, and classical assumption tests. The instrument was valid (corrected item–total r = .557–.736) and reliable (Cronbach's alpha = .766–.859). Overconfidence (β = .203; p < .001), loss aversion (β = .148; p = .005), and optimism bias (β = .138; p = .009) each have a positive and significant partial effect on investment decisions, and the three variables are jointly significant (F = 11.127; p < .001; adjusted R^2 = .083). Overconfidence is the strongest predictor, although the modest explanatory power shows that other factors also shape investment decisions. Investors, platform providers, and regulators are encouraged to strengthen bias-aware financial education and decision-support features.

Keywords: overconfidence; loss aversion; optimism bias; investment decision; behavioral finance; Garut Regency

1 Introduction

Retail participation in the Indonesian capital market has expanded at an unprecedented pace. According to data cited by Antara (2026b), the number of investors rose from 14.87 million in 2024 to 20.35 million at the end of 2025 and reached 30.06 million in July 2026, which the Financial Services Authority (OJK) reported as growth of 47.63% year to date (Antara, 2026a). Young people drive much of this growth: OJK recorded that 54.20% of investors in September 2025 were younger than 30 (Infobanknews, 2025), and the Indonesian Central Securities Depository (KSEI) reported that investors in West Java are dominated by Generation Z and millennials (RMOL Jabar, 2026). Digital investment platforms, such as online mutual fund marketplaces, stock trading applications, and crypto exchanges, lower the cost of entry and give newcomers access to markets from a smartphone, including in regions outside the large metropolitan areas.

However, the growth in the number of investors does not guarantee the quality of their decisions. The value of assets recorded in the capital market fell by 22% to IDR 8,261 trillion in August 2026 even though the number of investors kept rising (Bisnis.com, 2026), and KSEI itself has stated that improving investor quality is as important as increasing the number of investors (Bisnis.com, 2025). A large cohort of young investors with short investment histories is therefore facing its first period of market stress. In that setting, the way people form beliefs about their own ability, about losses, and about future returns becomes a decisive element of how they allocate funds and manage risk.

Garut Regency illustrates this situation. Publicly available investor statistics are generally not disaggregated to the regency level, so the local picture has to be drawn from primary data. The 336 fintech investors surveyed in this study, who live in 40 sub-districts of the regency, have a mean age of 22.4 years (range 18–27); 54.5% use online mutual funds, 40.8% invest in stocks, and 33.9% hold crypto assets (some use more than one instrument). This profile is consistent with the national pattern of young, platform-based investors and shows that retail investing is no longer limited to big cities.

Traditional finance assumes that investors process information rationally, whereas behavioral finance shows that systematic psychological biases shape financial choices (Barberis & Thaler, 2003; Kahneman & Tversky, 1979). Three biases are particularly relevant for individual investors. Overconfidence makes investors overrate the precision of their knowledge and has been linked to heavier trading (Barber & Odean, 2001; Statman et al., 2006). Loss aversion makes losses weigh more heavily than equivalent gains and underlies the disposition effect (Odean, 1998; Tversky & Kahneman, 1992). Optimism bias leads people to believe that good outcomes are more likely, and bad outcomes less likely, for themselves than for others (Sharot, 2011; Weinstein, 1980).

Empirical studies agree that these biases matter, but the direction and strength of their relationship with investment decisions vary across samples and measures (Kumar & Goyal, 2015; Metawa et al., 2019; Rahman & Gan, 2020). Studies in Indonesia have mostly examined investors in large cities or among students (Ainia & Lutfi, 2019; Kartini & Nahda, 2021), and evidence from non-metropolitan regencies is still scarce. Addressing this gap, the study asks whether overconfidence, loss aversion, and optimism bias, each measured through two dimensions and four indicators, have a positive and significant effect on the investment decisions of fintech investors in Garut Regency, both partially and simultaneously. The findings are expected to help investors, platform providers, regulators, and educators design bias-aware investor protection and education.

2 Literature Review

2.1 Behavioral Finance and Investment Decision

Behavioral finance integrates psychology into financial decision-making and explains why investors depart systematically from the rational model (Baker & Nofsinger, 2010; Barberis & Thaler, 2003). Prospect theory, the foundation of the field, describes choices under risk with reference-dependent values, loss aversion, and subjective probability weighting (Kahneman & Tversky, 1979). Biases appear when investors rely on heuristics under uncertainty and when they have a strong sense of control over their own choices (Kahneman & Riepe, 1998; Pompian, 2012). In this study, investment decision refers to the way investors structure and control their portfolios. It has two dimensions. The asset allocation decision concerns how funds are distributed across instruments according to risk profile and goals, a principle rooted in portfolio theory (Markowitz, 1952), and includes the use of a disciplined cut-loss strategy. The risk management decision concerns regular portfolio rebalancing aligned with financial goals and independent analysis

before a transaction is made. Higher scores therefore indicate decisions that are more deliberate, rule-based, and self-directed.

2.2 Overconfidence

Overconfidence is the tendency to overestimate one's knowledge, ability, or the accuracy of one's information (Moore & Healy, 2008). It has two dimensions in this study. Miscalibration refers to overestimating the accuracy of market predictions and believing that one's investment capability exceeds that of peers. The better-than-average effect refers to believing that one's return predictions are more accurate than realized outcomes and holding confidence in superior investment knowledge. Gervais and Odean (2001) show that early successes can make traders overconfident, and subsequent studies connect overconfidence to high trading volume (Glaser & Weber, 2007; Statman et al., 2006), to miscalibrated beliefs even among professionals (Ben-David et al., 2013).

2.3 Loss Aversion

Loss aversion means that the pain of a loss is larger than the pleasure of an equally sized gain. Tversky and Kahneman (1992) estimated a loss-aversion coefficient of about 2.25. The first dimension, perceived loss sensitivity, covers high anxiety about potential losses and the reluctance to realize losses by holding losing investments. The second dimension, the disposition effect, covers selling profitable investments prematurely and the feeling that loss pain exceeds gain pleasure (Odean, 1998; Shefrin & Statman, 1985; Weber & Camerer, 1998). Because evaluating results frequently makes losses more visible, loss aversion can also appear as myopic behavior (Benartzi & Thaler, 1995).

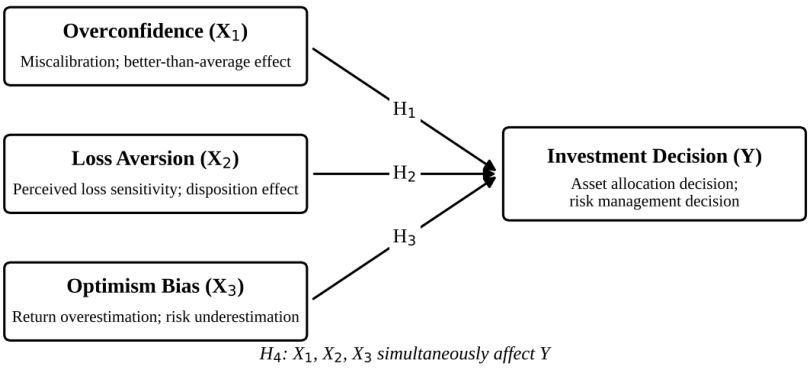
2.4 Optimism Bias

Optimism bias is the tendency to expect better outcomes for oneself than the objective probability warrants (Weinstein, 1980; Sharot, 2011). Its first dimension, return overestimation, covers expecting returns above market averages and underestimating the personal probability of investment loss. Its second dimension, risk underestimation, covers being more optimistic about one's own portfolio than that of others and believing that adverse outcomes apply less to oneself. Optimistic people tend to take more economic risk and to commit more to their plans (Puri & Robinson, 2007).

2.5 Hypothesis Development

Evidence on the direction of these relationships is mixed. Overconfidence is positively related to investment decisions in several Indonesian studies (Ainia & Lutfi, 2019; Kartini & Nahda, 2021; Pratiwi & Puspawati, 2022) and significantly affects decisions in Egypt (Metawa et al., 2019), but Rahman and Gan (2020) report a negative relationship among Malaysian Generation Y investors and Pratiwi and Leon (2019) find no effect. Loss aversion has a positive influence in Gunawan and Wiyanto (2022) and Kartini and Nahda (2021) but no effect in Ainia and Lutfi (2019). Optimism has a positive influence in Pratiwi and Leon (2019) and is significant in Kartini and Nahda (2021). Because investment decision in this study captures deliberate, rule-based, and self-directed decisions, the theoretical argument is that each bias increases the willingness to build and control a portfolio actively. The following hypotheses are therefore proposed (Figure 1):
H_1: Overconfidence has a positive and significant effect on investment decisions. **H_2**: Loss aversion has a positive and significant effect on investment decisions. **H_3**: Optimism bias has a positive and significant effect on investment decisions. **H_4**: Overconfidence, loss aversion, and optimism bias simultaneously have a significant effect on investment decisions.

Figure 1: Conceptual framework



3 Research Method

3.1 Research Design, Population, and Sample

This study uses a quantitative explanatory design to test the causal relationship between three independent variables (overconfidence, loss aversion, and optimism bias) and one dependent variable (investment decision) (Sugiyono, 2019). The population is individual investors in Garut Regency who invest through fintech platforms. Purposive sampling was applied, with respondents required to live in Garut Regency and to be actively investing through at least one digital platform. The final sample consists of 336 respondents from 40 sub-districts. This number exceeds the minimum suggested for multiple regression, $N \geq 50 + 8m$, which equals 74 for three predictors (Green, 1991), and the ratio of at least 20 observations per predictor recommended by Hair et al. (2019).

3.2 Variables and Measurement

Each variable was measured with four statements (two indicators for each of two dimensions) on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Table 1 presents the operationalization. Total scores range from 4 to 20, and the mean score per item is classified as very low (1.00–1.80), low (1.81–2.60), moderate (2.61–3.40), high (3.41–4.20), or very high (4.21–5.00).

Table 1: Operationalization of variables

Variable	Dimension	Indicator	Code
Overconfidence (X_1)	Miscalibration	Overestimating the accuracy of market predictions	OC1
		Believing that investment capability exceeds that of peers	OC2
	Better-than-average effect	Return predictions are more accurate than realized	OC3
		Confidence in superior investment knowledge	OC4
Loss Aversion (X_2)	Perceived loss sensitivity	High anxiety about potential investment losses	LA1
		Holding losing investments to avoid realizing losses	LA2
	Disposition effect	Selling profitable investments prematurely	LA3
		Loss pain felt greater than equivalent gain pleasure	LA4
Optimism Bias (X_3)	Return overestimation	Expecting returns to exceed market averages	OB1
		Underestimating personal investment loss probability	OB2
	Risk underestimation	More optimistic about own portfolio than others	OB3
		Believing adverse outcomes apply less to oneself	OB4
Investment Decision (Y)	Asset allocation decision	Allocating instruments based on risk profile and goals	ID1
		Applying a disciplined cut-loss strategy	ID2
	Risk management decision	Regular portfolio rebalancing aligned with financial goals	ID3
		Independent analysis prior to investment decisions	ID4

3.3 Data Analysis

Data were processed with SPSS. Instrument validity was tested with corrected item–total correlations, with an item regarded as valid when r exceeds the critical value of .107 (n = 336; α = .05), and reliability was tested with Cronbach's alpha, with values above .70 considered acceptable (Ghozali, 2018; Nunnally & Bernstein, 1994). Classical assumptions were checked for normality of residuals (Kolmogorov–Smirnov and Shapiro–Wilk), multicollinearity (tolerance and variance inflation factor), heteroscedasticity (Breusch–Pagan), and autocorrelation (Durbin–Watson) (Gujarati & Porter, 2009). The hypotheses were tested with the multiple linear regression model:

$$ID = \alpha + \beta_1 OC + \beta_2 LA + \beta_3 OB + \varepsilon \quad ...(1)$$

where ID is investment decision, OC is overconfidence, LA is loss aversion, OB is optimism bias, α is the constant, β is the regression coefficient, and ε is the error term. The partial effects were tested with the t-test, the simultaneous effect with the F-test, and the model's explanatory power with R^2 and adjusted R^2 at a 5% significance level. Effect size was interpreted with Cohen's f^2 (Cohen, 1988).

4 Results and Discussion

4.1 Respondent Profile

Table 2 summarizes the profile of the 336 respondents. Women make up 51.8% of the sample. Most respondents hold a bachelor's degree (S1; 49.4%), and the largest income group earns IDR 2–5 million (35.4%). The age range is 18–27 years (mean = 22.4; SD = 2.9), so the sample consists mainly of young investors. Around 46.7% have invested for more than one year, and 67.3% transact at least three times in the reference period, which shows that the respondents are active rather than passive investors.

Table 2: Respondent profile (N = 336)

Gender	**n**	**%**	**Length of investing**	**n**	**%**
Female	174	51.8	< 6 months	83	24.7
Male	162	48.2	6–12 months	96	28.6
Education	**n**	**%**	1–2 years	105	31.2
SMA/SMK	103	30.7	> 2 years	52	15.5
D3	53	15.8	**Transaction frequency**	**n**	**%**
S1	166	49.4	1–2 times	110	32.7
S2	14	4.2	3–5 times	131	39.0
Income (IDR)	**n**	**%**	6–10 times	66	19.6
< 2 million	104	31.0	> 10 times	29	8.6
2–5 million	119	35.4	**Instrument used***	**n**	**%**
5–10 million	83	24.7	Mutual funds	183	54.5
> 10 million	30	8.9	Stocks	137	40.8
			Crypto	114	33.9

Source: primary data (processed). *Multiple responses allowed; percentages are calculated from N = 336.

4.2 Instrument Testing and Descriptive Statistics

All 16 items are valid: the corrected item–total correlations range from 0.557 to 0.736, far above the critical value of .107. All variables are also reliable, with Cronbach's alpha above .70 (Table 3). The mean item scores show that overconfidence is the highest of the three biases (M = 3.41, high), followed by optimism bias (M = 3.36) and loss aversion (M = 3.30), both moderate. Investment decision is also moderate (M = 3.25). At the dimension level, the scores are very similar: miscalibration 3.41 and better-than-average effect 3.41; perceived loss sensitivity 3.28 and disposition effect 3.32; return overestimation 3.36 and risk underestimation 3.35; asset allocation 3.25 and risk management 3.26. Respondents therefore tend to describe themselves as fairly confident, moderately loss-sensitive, and moderately optimistic, while their portfolio discipline is moderate rather than strong.

Table 3: Validity, reliability, and descriptive statistics

Variable	Items	Corrected item–total r	Cronbach's α	Mean item	Category
Overconfidence	4	.602–.670	.810	3.41	High
Loss aversion	4	.685–.736	.859	3.30	Moderate
Optimism bias	4	.644–.669	.830	3.36	Moderate
Investment decision	4	.557–.582	.766	3.25	Moderate

Source: primary data (processed).

4.3 Classical Assumption Tests

The residuals are normally distributed (Kolmogorov–Smirnov p = .672; Shapiro–Wilk p = .313). Tolerance values are .990–.996 and VIF values are 1.004–1.010, so multicollinearity is absent; the correlations among the three biases are also very low ($r \leq .088$). The Breusch–Pagan test (p = .365) indicates homoscedasticity, and the Durbin–Watson statistic (1.866) lies close to 2, indicating no autocorrelation. The data therefore satisfy the assumptions of the regression model.

4.4 Regression Results

Table 4 presents the regression estimates. The model is significant ($F(3, 332) = 11.127$; $p < .001$), which supports H_4. The coefficient of determination is $R^2 = .091$ (adjusted $R^2 = .083$), which means that the three biases jointly explain 9.1% of the variation in investment decisions, and the remaining 90.9% is explained by other factors. In terms of Cohen's (1988) $f^2 = .10$, the overall effect is small to medium. The estimated equation is: $ID = 6.934 + 0.194OC + 0.133LA + 0.125OB$.

Table 4: Multiple linear regression results (dependent variable: investment decision)

Variable	B	Std. error	Beta	t	Sig.	95% CI of B	Decision
(Constant)	6.934	1.066		6.503	.000	4.836; 9.031	
Overconfidence	.194	.050	.203	3.867	.000	.096; .293	H_1 accepted
Loss aversion	.133	.047	.148	2.824	.005	.040; .225	H_2 accepted
Optimism bias	.125	.048	.138	2.634	.009	.032; .219	H_3 accepted

Source: SPSS output (processed). F = 11.127 (Sig. = .000); R = .302; R^2 = .091; adjusted R^2 = .083; standard error of the estimate = 2.335; N = 336; critical t (df = 332) = 1.967.

4.5 Relationships at the Dimension and Indicator Level

Because each variable is measured through two dimensions and four indicators, the discussion of H_1–H_3 is organized around the way each bias dimension connects with the two dimensions of investment decision: asset allocation (ID1, ID2) and risk management (ID3, ID4). Table 5 reports the supporting dimension-level correlations. These coefficients are supplementary zero-order results computed from the same data; they are not part of the main regression, they are based on two-item composites, and they are interpreted as patterns rather than as causal effects.

Table 5: Correlations between bias dimensions and investment decision dimensions (N = 336)

Bias dimension	Indicators	Asset allocation (ID1–ID2)	Risk management (ID3–ID4)
Miscalibration (X_1)	OC1, OC2	.148**	.182**
Better-than-average effect (X_1)	OC3, OC4	.187**	.204**
Perceived loss sensitivity (X_2)	LA1, LA2	.135*	.181**
Disposition effect (X_2)	LA3, LA4	.076 (ns)	.185**
Return overestimation (X_3)	OB1, OB2	.150**	.132*
Risk underestimation (X_3)	OB3, OB4	.130*	.118*

Source: primary data (processed). Pearson r; * p < .05; ** p < .01; ns = not significant.

4.6 Overconfidence and Investment Decision (H1)

Overconfidence has a positive and significant partial effect on investment decisions (B = .194; β = .203; t = 3.867; p < .001), so H_1 is accepted. It is the strongest of the three biases, and the only one that is significantly related to both decision dimensions at the dimension level (Table 5). Respondents report a high level of overconfidence (M = 3.41), and the logic of the effect becomes clearer when each dimension is followed through the decision process.

Miscalibration (OC1, OC2) and the decision process. Miscalibrated investors place too narrow a confidence interval around their forecasts (Ben-David et al., 2013; Moore & Healy, 2008). An investor who believes that the accuracy of market predictions is high (OC1) will treat a forecast as precise enough to justify a specific cut-loss level (ID2; r = .15, p = .005) and to rely on personal analysis before trading (ID4; r = .15, p = .007), whereas the link with the initial allocation (ID1) is weak and not significant (r = .06). This suggests that miscalibration is expressed more in how investors implement and control positions than in how they first split their funds. The belief that one's capability exceeds that of peers (OC2) is related most strongly to independent analysis (ID4; r = .17, p = .002): an investor who regards peers as less capable has little reason to follow them and therefore does their own analysis. At the dimension level the correlations are r = .15 with asset allocation and r = .18 with risk management.

Better-than-average effect (OC3, OC4) and the decision process. People tend to rate themselves above average on skill-related tasks (Svenson, 1981), and Gervais and Odean (2001) show how early success can feed this belief. This dimension has the strongest relationship with the decision dimensions (r = .19 with asset allocation and r = .20 with risk management). Confidence in superior investment knowledge (OC4) has the highest indicator-level correlation in the data, with the cut-loss strategy (ID2; r = .22, p < .001), and it is also related to independent analysis (ID4; r

= .19, p = .001): investors who trust their own judgement are willing to set personal rules and to act on them. Believing that one's return predictions are more accurate than realized outcomes (OC3) is related to ID2 (r = .15), ID3 (r = .13), and ID4 (r = .14), which is consistent with the idea that rebalancing (ID3) requires confidence in a target allocation. Fintech platforms may reinforce these beliefs through real-time information, simple order placement, and gamified interfaces that encourage action (Barber et al., 2022).

Consistency with previous studies. The positive result agrees with studies of Indonesian investors (Ainia & Lutfi, 2019; Kartini & Nahda, 2021; Pratiwi & Puspawati, 2022) and with evidence that overconfidence significantly affects investment decisions in Egypt (Metawa et al., 2019). The literature is not unanimous, however. Rahman and Gan (2020) report a negative relationship among Malaysian Generation Y investors, and Pratiwi and Leon (2019) find no effect. A plausible reason is the way the dependent variable is defined: when investment decision is measured as deliberate, self-directed process, as in this study, overconfidence tends to raise it, whereas studies focusing on trading outcomes emphasize costs such as excessive trading and under-diversification (Barber & Odean, 2000; Goetzmann & Kumar, 2008). The coefficient here therefore indicates more active and self-directed decisions, not necessarily better performance.

4.7 Loss Aversion and Investment Decision (H2)

Loss aversion also has a positive and significant partial effect (B = .133; β = .148; t = 2.824; p = .005), so H_2 is accepted. According to prospect theory, a loss is weighted more heavily than a gain of equal size (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), so investors with strong loss aversion regard a poorly controlled portfolio as a direct threat. A supplementary regression on the two decision dimensions shows that the effect is concentrated in risk management (B = .088; p = .001) and is weaker and not significant for asset allocation (B = .045; p = .087), which agrees with the pattern below.

Perceived loss sensitivity (LA1, LA2) and the decision process. Anxiety about potential losses (LA1) makes the downside salient and motivates protective routines; it is related to rebalancing (ID3; r = .12, p = .034) and to cut-loss discipline (ID2; r = .11, p = .039). The reluctance to realize losses (LA2) shows a more interesting pattern: it is positively related to ID3 (r = .19, p = .001), ID4 (r = .17, p = .002), and ID2 (r = .16, p = .002). This is not a contradiction. Investors who feel losses acutely both find it hard to sell a losing position (Odean, 1998; Shefrin & Statman, 1985) and see the value of explicit rules that remove the decision from the moment of pain, which is the logic of pre-set stop-loss rules (Kaminski & Lo, 2014). At the dimension level the correlations are r = .14 with asset allocation and r = .18 with risk management.

Disposition effect (LA3, LA4) and the decision process. Selling profitable investments prematurely (LA3) and feeling that loss pain exceeds gain pleasure (LA4) are related to risk management (ID3 and ID4; r = .12–.15, p < .05) but not to the initial asset allocation (r = .08 at the dimension level, not significant). The reason is that these indicators describe behavior after a position has been taken: investors keep monitoring prices, protect gains, and review the portfolio often, a pattern that raises risk-management activity (Benartzi & Thaler, 1995; Dhar & Zhu, 2006), but it says little about how instruments were chosen originally. The result should not be read as a benefit of the disposition effect itself, because selling winners early and holding losers can reduce returns (Odean, 1998).

Consistency with previous studies. Gunawan and Wiyanto (2022) and Kartini and Nahda (2021) also report a significant positive influence of loss aversion on investment decisions, whereas Ainia and Lutfi (2019) find no effect. The modest coefficient (95% CI of B: .040 to .225) fits this mixed

record, and since discipline is self-reported, the execution of rules needs to be confirmed with actual trading data.

4.8 Optimism Bias and Investment Decision (H3)

Optimism bias has a positive and significant partial effect (B = .125; β = .138; t = 2.634; p = .009), so H_3 is accepted. Its coefficient is the smallest of the three. The mechanism runs through expectations and commitment: people who expect good outcomes for themselves (Weinstein, 1980; Sharot, 2011) are more willing to commit to a plan, and optimists have been shown to take more economic risk and to commit more to their choices (Puri & Robinson, 2007). The supplementary regressions show a significant association with both asset allocation (B = .069; p = .010) and risk management (B = .057; p = .033).

Return overestimation (OB1, OB2) and the decision process. Expecting returns above the market average (OB1) is related to cut-loss discipline (ID2; r = .15, p = .005) and independent analysis (ID4; r = .16, p = .004): an investor who aims to outperform needs a structured process to do so. Underestimating the personal probability of loss (OB2) is related only to asset allocation (ID1; r = .14, p = .011) and not to the protective indicators (r = .08, not significant). This is logically consistent: when loss feels unlikely, an investor is comfortable spreading funds across instruments, including riskier ones, but sees little need for protective rules. At the dimension level the correlations are r = .15 with asset allocation and r = .13 with risk management.

Risk underestimation (OB3, OB4) and the decision process. This dimension has the weakest correlations (r = .13 with asset allocation and r = .12 with risk management). Believing that adverse outcomes apply less to oneself (OB4) is related to ID1 (r = .15, p = .005), ID2 (r = .13, p = .015), and ID4 (r = .13, p = .015), consistent with the view that unrealistic optimism supports commitment to investing (Weinstein & Klein, 1996). Being more optimistic about one's own portfolio than about others' (OB3) is not significantly related to any decision indicator. A plausible explanation is that OB3 is a social comparison and does not directly concern the choices that ID1–ID4 describe.

Consistency with previous studies. The positive result agrees with Pratiwi and Leon (2019), Kartini and Nahda (2021), and Khan et al. (2017), who relate optimism to investors' financial decisions. Its practical risk is that optimists may prepare insufficiently for adverse markets, which is relevant in 2026 when recorded asset values fell by 22% (Bisnis.com, 2026).

4.9 Simultaneous Effect and Implications (H4)

The three biases jointly have a significant effect on investment decisions (F = 11.127; p < .001), but they explain only 9.1% of its variance. The correlations among the biases are very low (r = .040–.088) and the VIF values are almost 1, so each bias is associated with investment decisions in its own, additive way. Taken together, the dimension-level evidence shows three distinct profiles: overconfidence is connected with both asset allocation and risk management through both of its dimensions; loss aversion is connected mainly with risk management; and optimism bias is connected more weakly with both. With 336 respondents even small effects reach significance, so the practical size of each effect should be judged from the standardized coefficients (.138–.203) and f^2 = .10. The remaining 90.9% is most likely related to other factors, such as financial literacy (Fachrudin & Fachrudin, 2016; Lusardi & Mitchell, 2014), herding behavior, risk perception, financial experience, and income.

Three implications follow. For investors, recognizing one's own biases, keeping a decision journal, and setting rules for allocation, cut-loss, and rebalancing before entering a position can

turn the motivational force of these biases into disciplined behavior. For platform providers, risk-profile questionnaires, feedback on forecast accuracy compared with actual outcomes, rebalancing reminders, and limits on gamified features can support calibration. For regulators and educators, including OJK, KSEI, the regional government, and universities in Garut, investor education in the sub-districts should address behavioral biases directly in addition to product knowledge, because the investor base is young and still growing.

5 Conclusions

Overconfidence, loss aversion, and optimism bias each have a positive and significant partial effect on the investment decisions of fintech investors in Garut Regency, and the three variables are jointly significant. Overconfidence has the strongest effect ($\beta = .203$), followed by loss aversion ($\beta = .148$) and optimism bias ($\beta = .138$). The model explains 9.1% of the variance (adjusted $R^2 = .083$), so the findings should be interpreted as evidence of a consistent but modest association; the biases are associated with more active, rule-based, and self-directed decisions, not with better investment performance.

Investors are advised to calibrate their confidence against actual results, to define allocation, cut-loss, and rebalancing rules in advance, and to test optimistic return expectations with downside scenarios. Platform providers should build calibration feedback and risk-awareness nudges into their applications, and regulators and educators should include behavioral-bias modules in investor education programs in the regency. Future studies are encouraged to add financial literacy, herding behavior, risk perception, and financial experience as additional predictors or moderators, to use probability sampling and actual trading records, and to apply longitudinal designs so that causal interpretation can be strengthened. This study is limited by its cross-sectional, self-reported data and by a non-probability sample.

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