

Risk Tolerance as the Invisible Hand: Rethinking the Causal Architecture of Behavioral Biases in Individual Investment Decision-Making

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Abstract

This study challenges the prevailing causal architecture of behavioral finance, in which loss aversion, overconfidence, and FOMO are treated as independent determinants of risk tolerance as a situational outcome. Drawing on Big Five Trait Theory, Prospect Theory, and Mischel and Shoda's (1995) person–situation interactionist framework, it advances an alternative model in which financial risk tolerance functions as a stable dispositional antecedent through which situational biases operate as transmission mechanisms. Primary data were collected from 140 active retail investors in Indonesia via snowball sampling from digital investor communities, with PLS-SEM employed for hypothesis testing. Results support three of four hypotheses: risk tolerance exerts a significant positive direct effect on investment decisions, and overconfidence and FOMO each function as significant mediating channels. The loss aversion pathway is not supported — interpreted in light of the sample's digitally-engaged, high-tolerance profile, wherein social and momentum forces appear to override loss aversion's constraining effect when stronger mediators are simultaneously active. These findings contribute a dispositional reframing of the investor behavioral model with direct implications for risk profiling instruments, financial advisor calibration, and the design of targeted behavioral interventions.

Keywords: risk tolerance, behavioral finance, FOMO, loss aversion, overconfidence, investment decisions, PLS-SEM, Indonesia

1. Introduction

In the winter of 2021, an army of retail investors on Reddit's WallStreetBets forum collectively drove GameStop's share price from approximately \$20 to nearly \$483 in a matter of weeks — a market event that defied every prescription of classical finance theory (Barber et al., 2022). Analysts scrambled for explanations. Some pointed to herding behavior. Others to overconfidence, to social contagion, to the intoxicating Fear of Missing Out (FOMO) pulsating through social media feeds in real time. These explanations were not wrong — but they were, in a precise and consequential sense, incomplete. They described what investors did without adequately accounting for who they already were before the first share was purchased. The meme stock phenomenon was not simply a story of situational forces overriding rational judgment; it was also a story of investors with varying dispositional risk tolerances responding to identical situational triggers in radically divergent ways. Some doubled down. Others cashed out early. Many never participated at all. The psychological biases were the same; the baseline

dispositions were not.

This divergence strikes at the heart of a structural assumption that has quietly governed behavioral finance research for decades. Since Kahneman & Tversky (1979) foundational articulation of Prospect Theory in *Econometrica* — and the subsequent proliferation of bias-centric models tracing overconfidence (Barber & Odean, 2001), loss aversion (Shefrin & Statman, 1985), and FOMO (Gupta & Shrivastava, 2022) as primary drivers of irrational investment behavior — the dominant causal logic of the field has positioned psychological biases as independent variables whose cumulative force produces risk tolerance as a downstream, situationally-negotiated outcome. In this model, risk tolerance is not something an investor brings to the market; it is something the market, mediated by psychological distortions, creates in the moment. The investor, in effect, arrives without a backbone.

The empirical record, however, tells a more nuanced story. A growing body of evidence in financial psychology and investor profiling research has demonstrated, with increasing robustness, that risk tolerance is best understood not as a situational construction but as a moderately stable psychological trait — a dispositional property of the investor that persists across market conditions, life contexts, and decision environments (Morningstar, 2022; Mottola & Kieffer, 2024). Personality-based studies have confirmed that stable Big Five traits — particularly openness to experience, neuroticism, and conscientiousness — are significant predictors of financial risk tolerance and investment behavior (Filomena & Corrêa Piccolini, 2019; Mansfield & Pinto, 2021). The CFA Institute's definitive risk profiling framework similarly distinguishes the investor's "*behavioural willingness to take risk*" as a stable emotional characteristic that "*can be even more important for practitioners to understand than objective economic circumstances*" (Klement, 2018). If risk tolerance is, in fact, a stable trait that investors carry into every decision context, then treating it as an output of situational biases is not merely theoretically unsatisfying — it is structurally incorrect.

It is precisely this structural incorrectness that the present study seeks to remedy. Departing from the conventional causal architecture, this research proposes and empirically tests an alternative model in which risk tolerance functions as a stable, dispositional antecedent — a pre-existing psychological baseline through which situational biases operate. Specifically, the study positions FOMO, loss aversion, and overconfidence not as independent forces that shape an investor's risk appetite, but as situational mediators — psychological mechanisms through which a person's underlying risk disposition is translated into observable investment decisions. In this reconceived framework, it is not that overconfident investors become tolerant of risk; rather, risk-tolerant investors are more likely to express their tolerance through overconfident behavior when situational triggers are present. The causal arrow does not run from bias to tolerance; it runs from tolerance through bias to behavior.

The urgency of this reframing is amplified by the dramatic transformation of the retail investment landscape over the past decade. The democratization of financial markets through mobile trading platforms, the proliferation of investment-related social media content, and the explosive growth of cryptocurrency markets have collectively created an environment in which

FOMO is not an occasional psychological aberration but a near-permanent ambient pressure on decision-making (Przybyla & Kowalski, 2023; Sievert & Fischer, 2023). Studies confirm that young, digitally-native investors — now among the most significant participant groups in global equity and crypto markets — exhibit heightened susceptibility to all three of the biases under investigation (Bo, 2023; Worthington & Yin-Fah, 2023). In this context, models that fail to account for investors' stable risk dispositions will consistently misattribute behavioral variation: what appears to be the effect of FOMO may, in reality, be the expression of a pre-existing high-tolerance disposition through a FOMO-shaped channel.

Despite the theoretical and practical significance of this distinction, no existing study in the behavioral finance literature has empirically tested a model in which risk tolerance simultaneously precedes and conditions the mediating roles of FOMO, loss aversion, and overconfidence in investment decision-making. Recent mediation studies have examined the serial mediation of overconfidence and disposition effects between heuristic biases and investment outcomes (Shunmugasundaram & Sinha, 2025) others have explored FOMO's mediating role in the loss aversion–investment decision chain (Chi et al., 2025; Gupta & Shrivastava, 2022). Yet in each of these architectures, risk tolerance either appears as an outcome, a control, or an absence. The precise causal model proposed here — Risk Tolerance → {FOMO, Loss Aversion, Overconfidence} → Investment Decisions — remains untested. This is the gap the present study fills.

This study makes three interrelated contributions to the behavioral finance literature. First, it advances a dispositional reframing of the investor behavioral model, integrating insights from personality psychology and financial risk-profiling research to establish risk tolerance as a theoretically legitimate and empirically tractable antecedent variable. Second, it tests a novel mediating architecture in which FOMO, loss aversion, and overconfidence function as conditional transmission mechanisms — converting stable dispositional risk tolerance into context-specific investment behavior. Third, it provides a framework with direct practical applications for the design of investor risk profiling instruments, the calibration of financial advisory services, and the construction of behavioral interventions targeted at specific investor dispositional profiles rather than generic bias correction (Ahmed et al., 2022; CFA Institute, 2018).

The remainder of this paper is organized as follows. Section 2 reviews the theoretical foundations of risk tolerance, Prospect Theory, and the behavioral finance literature on FOMO, loss aversion, and overconfidence, culminating in the articulation of the hypothesized causal model. Section 3 describes the research methodology, including instrument design, sampling strategy, and the structural equation modeling approach employed for hypothesis testing. Section 4 presents the empirical results and tests the proposed mediating structure. Section 5 discusses the findings in relation to existing theory, outlines the practical implications for investor profiling and intervention design, acknowledges the study's limitations, and identifies directions for future research. The discussion returns, ultimately, to the question raised by the winter of 2021: when markets tremble and opportunity seems to beckon from every screen, what is it that separates the investor who acts from the one who waits — and is that difference

made in the moment, or long before it?

2. Literature Review

This study is scaffolded upon three interlocking theoretical pillars: Prospect Theory, which explains how investors psychologically process gains and losses; the Big Five Trait Theory, which grounds risk tolerance as a stable dispositional property of the investor; and the Person–Situation Interactionist framework, which provides the formal logic for how a stable disposition translates into situationally-activated biases. Together, these frameworks constitute the theoretical architecture from which the study's causal model and each of its four hypotheses are derived.

2.1 Prospect Theory

Kahneman & Tversky (1979) Prospect Theory, published in *Econometrica*, remains the most influential descriptive account of how individuals make decisions under uncertainty. In contrast to Expected Utility Theory, which assumes rational, outcome-maximizing agents, Prospect Theory demonstrates that people evaluate outcomes relative to a reference point — and that this evaluation is fundamentally asymmetric. Losses are felt with roughly twice the psychological intensity of equivalent gains, a property the authors termed loss aversion. This asymmetry is not incidental; it is encoded in the shape of the value function itself, which is concave for gains and convex for losses, with a kink at the reference point (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Crucially, the theory's value function encodes a stable preference structure — characteristic of the decision-maker, not merely of the choice context. This dispositional quality provides the theoretical warrant for treating loss aversion not as a free-floating situational reaction but as an expression of an underlying risk disposition. Cross-cultural replication studies have confirmed Prospect Theory's empirical robustness at the 90 percent level across diverse national samples (Columbia Public Health, 2022), establishing it as the foundational descriptive model of investor behavior in this study.

2.2 Big Five Trait Theory and Risk Tolerance as Stable Disposition

The Five-Factor Model (McCrae & Costa, 1987) identifies five broad, cross-situationally stable personality dimensions — *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness*, and *Neuroticism* — that exhibit high test-retest reliability across time and life transitions. Their relevance to financial behavior lies in their demonstrated capacity to predict financial risk tolerance (FRT) beyond what demographic variables can explain. Mansfield & Pinto (2021) confirmed in a large UK retail investor study that personality traits are more important than transient emotions in determining risk attitudes. Filomena & Corrêa Piccolini (2019) found that investors with higher IPA-measured risk tolerance and high openness to experience are significantly more likely to take higher-risk investment decisions. The CFA Institute's risk profiling framework characterizes risk tolerance explicitly as a stable “*behavioural willingness to take financial risk*” that is more important for financial advisors to understand than objective economic circumstances (Klement, 2018). Morningstar's practitioner research further affirms that, when measured correctly, FRT “*remains remarkably stable*” across market conditions and

life events (Morningstar, 2022). The cumulative weight of this literature compels a respecification: FRT is a stable antecedent, not a situationally-produced output of psychological biases.

2.3 Person–Situation Interactionist Framework

The theoretical bridge between stable risk tolerance and its situational behavioral expression is provided by Mischel & Shoda (1995) cognitive-affective processing system (CAPS) model. Mischel's core insight is that *"personality is conceptualized as a stable system that mediates how the individual selects, construes, and processes social information and generates social behaviors"* (p. 246). Behavioral variability across situations does not contradict dispositional stability; it reflects the activation of different facets of a stable architecture in response to different situational triggers — formalized as *"if-then"* behavioral signatures. In the present model, this logic generates a precise investment psychology application: risk tolerance (stable disposition) activates, to different degrees and in different market contexts, the three situational biases under investigation — loss aversion, overconfidence, and FOMO — each of which then transmits the dispositional signal into observable investment behavior. The model is thus not simply empirical; it is grounded in one of personality psychology's most robustly validated theoretical frameworks.

2.4 Hypothesis Development

The Direct Effect of Risk Tolerance on Investment Decisions. Beyond its role as the source variable in the mediating pathways, risk tolerance is expected to exert a significant direct effect on investment decisions. Investors with higher dispositional risk tolerance have internalized a broader psychological comfort with financial uncertainty, which manifests as greater willingness to initiate and sustain investment positions across asset classes and market conditions. Grable (2000) confirmed this relationship across demographic groups; Morningstar (2022) affirmed it in practitioner contexts; and Rawat (2024) provided empirical confirmation that risk tolerance significantly predicts investment decisions both directly and indirectly. The direct pathway captures the portion of risk tolerance's influence on investment behavior that is not transmitted through any of the three biases — the baseline dispositional engagement with investment.

H1: Risk tolerance has a significant positive direct effect on individual investors' investment decisions.

Risk Tolerance → Loss Aversion → Investment Decisions. Prospect Theory predicts that the psychological pain of loss is not uniform across investors; it is calibrated relative to the investor's reference point, which is itself shaped by their dispositional risk orientation. High-risk-tolerant investors enter market contexts with a broader psychological margin for loss — meaning loss aversion activates at a higher threshold and with lower intensity, freeing them to translate their tolerance into decisive investment action. Rawat (2024) provided direct empirical confirmation that risk tolerance fully mediates the loss aversion–investment decision relationship, establishing loss aversion as the conditional channel through which dispositional

tolerance reaches behavioral outcomes. Chi et al. (2025) corroborated this structure in a Southeast Asian investment context. The present study formally tests this mediation with loss aversion's role inverted from independent variable to situational transmission mechanism.

H2: Loss aversion mediates the relationship between risk tolerance and investment decisions, such that higher dispositional risk tolerance is associated with reduced loss aversion activation, which in turn produces more decisive investment behavior.

Risk Tolerance → Overconfidence → Investment Decisions. The pathway from dispositional risk tolerance through overconfidence to investment decisions is grounded in the Big Five–overconfidence linkage documented in recent empirical work. Investors with stable high-risk-tolerant personalities share key dispositional features — openness, lower neuroticism, higher extraversion — that independently predict overconfident self-assessment in financial contexts (IJAEB, 2024). High tolerance predisposes investors to optimistic self-appraisal of their market competence; this activated overconfidence then amplifies investment engagement beyond what the raw dispositional baseline would predict, producing the systematic excess trading documented by Barber & Odean (2001). The mediation logic is that overconfidence is not an independent cause of investment behavior but a dispositionally-activated amplifier: risk tolerance provides the motivational orientation, and overconfidence provides the cognitive justification that converts that orientation into specific investment commitments.

H3: Overconfidence mediates the relationship between risk tolerance and investment decisions, such that higher dispositional risk tolerance activates elevated financial self-confidence, which in turn significantly increases investment activity.

Risk Tolerance → FOMO → Investment Decisions. The FOMO mediation pathway operates through the social-cognitive dimension of investment behavior, which has been dramatically amplified by social media and digitally-connected trading environments. Investors with high dispositional risk tolerance maintain an active orientational readiness toward market opportunities; when social investment cues signal that others are profiting from a trend, this readiness is channeled through FOMO — the psychological urgency not to be left behind — into immediate investment action. Gupta & Shrivastava (2022) confirmed FOMO's partial mediating role in the loss aversion–investment decision chain; Worthington & Yin-Fah (2023) established that risk tolerance significantly moderates FOMO's influence on investment behavior. The present model respecifies this relationship: rather than risk tolerance moderating FOMO from the outside, risk tolerance activates FOMO from within, as the dispositional foundation that determines how intensely social investment signals are experienced as threat or opportunity. The FOMO pathway is theoretically expected to be especially strong among younger, digitally-native investor populations (Bo, 2023).

H4: FOMO mediates the relationship between risk tolerance and investment decisions, such that higher dispositional risk tolerance amplifies susceptibility to FOMO in response to social investment cues, which in turn directly precipitates investment decisions.

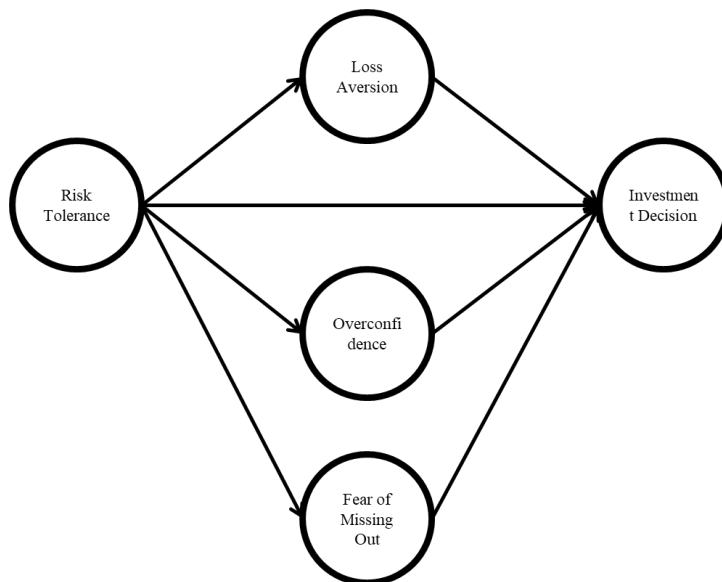


Figure 1. Conceptual Framework

3. Research Method

This study employs a quantitative, cross-sectional research design. This approach is warranted by the study's objective: to empirically test directional, theoretically-derived relationships among five latent constructs — Risk Tolerance, Loss Aversion, Overconfidence, FOMO, and Investment Decisions — through structural equation modeling. Primary data were collected via a structured, self-administered electronic questionnaire (Google Forms) comprising 28 Likert-scale items distributed across five constructs (Creswell, 2012).

Population and sample. The target population is individual retail investors in Indonesia who hold an active Single Investor Identification (SID) number registered with KSEI and who have executed at least one investment transaction in the past 12 months. As of 2024, registered individual investors in Indonesia exceed 12 million (Candra, 2025) constituting a large and dispersed population for whom the study's constructs are behaviourally relevant. A total of 140 respondents were obtained. This satisfies PLS-SEM adequacy under three independent criteria: Chin's (1998) 10-times rule (maximum four incoming paths on Investment Decisions requires a minimum of 40 observations); Kock & Hadaya's (2018) inverse square root method (100–140 sufficient for $\beta = 0.20$ – 0.30 at power = 0.80, $\alpha = 0.05$); and empirical benchmarks from comparable mediation studies in behavioral finance (Fauzi, 2022; Jain et al., 2023).

Respondents were recruited via snowball sampling — a non-probability technique in which qualified initial participants are invited to refer other eligible individuals from their networks (Berg, 2006; Memon et al., 2025). This technique is selected for three reasons specific to this study. First, no complete, publicly accessible sampling frame of Indonesian retail investors exists, rendering probability sampling technically infeasible (Sadler et al., 2010). Second, the behavioral constructs under investigation require respondents with genuine, direct investment

experience — a quality that random sampling from the general population cannot guarantee. Third, snowball sampling is well-precedented in quantitative behavioral finance research employing PLS-SEM (Kumar et al., 2023; Shunmugasundaram & Sinha, 2025). Sampling was initiated through 15 seed investors recruited from Indonesian investor communities (Stockbit, Bibit community groups, and investment-focused WhatsApp networks). Inclusion criteria required respondents to be: Indonesian residents; active SID holders; minimum 12 months of investment experience; aged 18 or above; and invested in at least one instrument (equities, mutual funds, bonds, or cryptocurrency). Of 158 questionnaires returned, 18 were excluded for incomplete responses, failed attention checks, or non-qualifying investor status, yielding the final analytic sample of $N = 140$.

Measurement Instrument. All constructs are operationalized as reflective latent variables, measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Items were adapted from validated, peer-reviewed instruments with established psychometric properties in behavioral finance and investment psychology (see Table 1). The questionnaire underwent back-translation for linguistic equivalence and was pilot-tested with 20 active investors prior to full deployment.

Table 1. Variable Measurement Framework

Variable	Role	Code	Indicator Item	Source
Risk Tolerance	<i>Antecedent</i>	RT1	Comfortable accepting portfolio uncertainty for higher returns.	Grable & Lytton (1999)
		RT2	Short-term investment fluctuations do not cause me undue anxiety.	Grable & Lytton (1999)
		RT3	Willing to invest in high-return assets even with significant loss risk.	Grable & Lytton (1999)
		RT4	Would hold position after a 20% portfolio loss rather than sell.	Li et al. (2021)
		RT5	I have a higher threshold for tolerating financial losses than most investors.	Klement (2018)
Loss Aversion	<i>Mediator 1</i>	LA1	Prospect of loss concerns me far more than missing equivalent gains.	Kahneman & Tversky (1979)
		LA2	I hold losing investments too long to avoid admitting a mistake.	Shefrin & Statman (1985)
		LA3	I focus more on avoiding losses than on maximizing gains.	Kahneman & Tversky (1979)
		LA4	I prefer a guaranteed smaller return over a higher-EV risky option.	Tversky & Kahneman (1992)
		LA5	A 10% loss causes more distress than a 10% gain causes satisfaction.	Dolder & Vandenbroucke (2024)

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Variable	Role	Code	Indicator Item	Source
		LA6	I reduce investment activity significantly after experiencing a loss.	Rawat (2024)
Overcon- fidence	<i>Mediator 2</i>	OC1	My investment analysis ability is above that of the average investor.	Barber & Odean (2001)
		OC2	I can accurately predict the future direction of researched assets.	Ritika & Kishor (2020)
		OC3	Good investment returns are primarily due to my own analytical skill.	Barber & Odean (2001)
		OC4	I trade frequently because I spot opportunities others miss.	Ritika & Kishor (2020)
		OC5	I rarely revise decisions even when contradictory information emerges.	Pan & Statman (2012)
		OC6	I have sufficient expertise to invest without professional advice.	Sharma & Prajapati (2024)
FOMO	<i>Mediator 3</i>	FM1	I urgently need to join trending investments before the opportunity disappears.	Przybylski et al. (2013)
		FM2	I feel anxious when I miss investment discussions happening in my social circle.	Shiva & Singh (2019)
		FM3	I worry that others achieve better returns from opportunities I am missing.	Chi et al. (2025)
		FM4	I have invested primarily to avoid being left out of a peer group trend.	Gupta & Shrivastava (2022)
		FM5	Fear of missing profit leads me to invest faster than I would otherwise prefer.	Worthington & Yin-Fah (2023)
Investment Decisions	<i>Outcome</i>	ID1	I actively allocate significant savings to equity or high-risk instruments.	Natasya et al. (2022)
		ID2	I make investment decisions quickly on identified opportunities.	Shahzad et al. (2024)
		ID3	I increase positions in currently well-performing assets.	Jain et al. (2023)
		ID4	I concentrate my portfolio in high-conviction assets over broad diversification.	Shunmugasundaram & Sinha (2025)
		ID5	I regularly review and adjust my	Jain et al. (2023)

Variable	Role	Code	Indicator Item	Source
			portfolio based on new market information.	
		ID6	I continue investing in volatile markets, trusting my risk management ability.	Ahmed et al. (2022)

Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. PLS-SEM is selected over CB-SEM because it does not require multivariate normality, is demonstrably superior for complex mediation estimation, and achieves robust results at moderate sample sizes (Hair et al., 2017; Sarstedt et al., 2020). Analysis proceeds in two stages. In Stage 1 (Outer Model), the measurement model is assessed for: indicator reliability (outer loadings ≥ 0.70); internal consistency (Cronbach's $\alpha \geq 0.70$; Composite Reliability 0.70–0.95); convergent validity (AVE ≥ 0.50). In Stage 2 (Inner Model), structural paths are estimated through bootstrapping (5,000 subsamples) with bias-corrected 95% confidence intervals. Mediation hypotheses (H2–H4) are tested via indirect path analysis, with significance confirmed when confidence intervals exclude zero (Sarstedt et al., 2020). Explanatory power is reported through R^2 (Hair et al., 2017).

4. Finding and Discussion

Outer Model Assessment (Measurement Model). The outer model assessment evaluates whether the indicators reliably and validly represent their designated latent constructs. The assessment proceeded in two iterative estimation rounds due to the identification of sub-threshold outer loading values in the initial estimation.

Initial Outer Model Estimation (Before Indicator Removal). In the first PLS-SEM estimation, outer loadings — which reflect the strength of the indicator–construct relationship — were examined for all 28 indicators against Hair et al.'s (2017) prescribed threshold of ≥ 0.70 . The initial estimation, visualized in Figure 2, revealed that 25 of 28 indicators satisfied the threshold. However, three indicators (RT5, OC2, ID3) returned loadings below 0.70 and were flagged for removal.

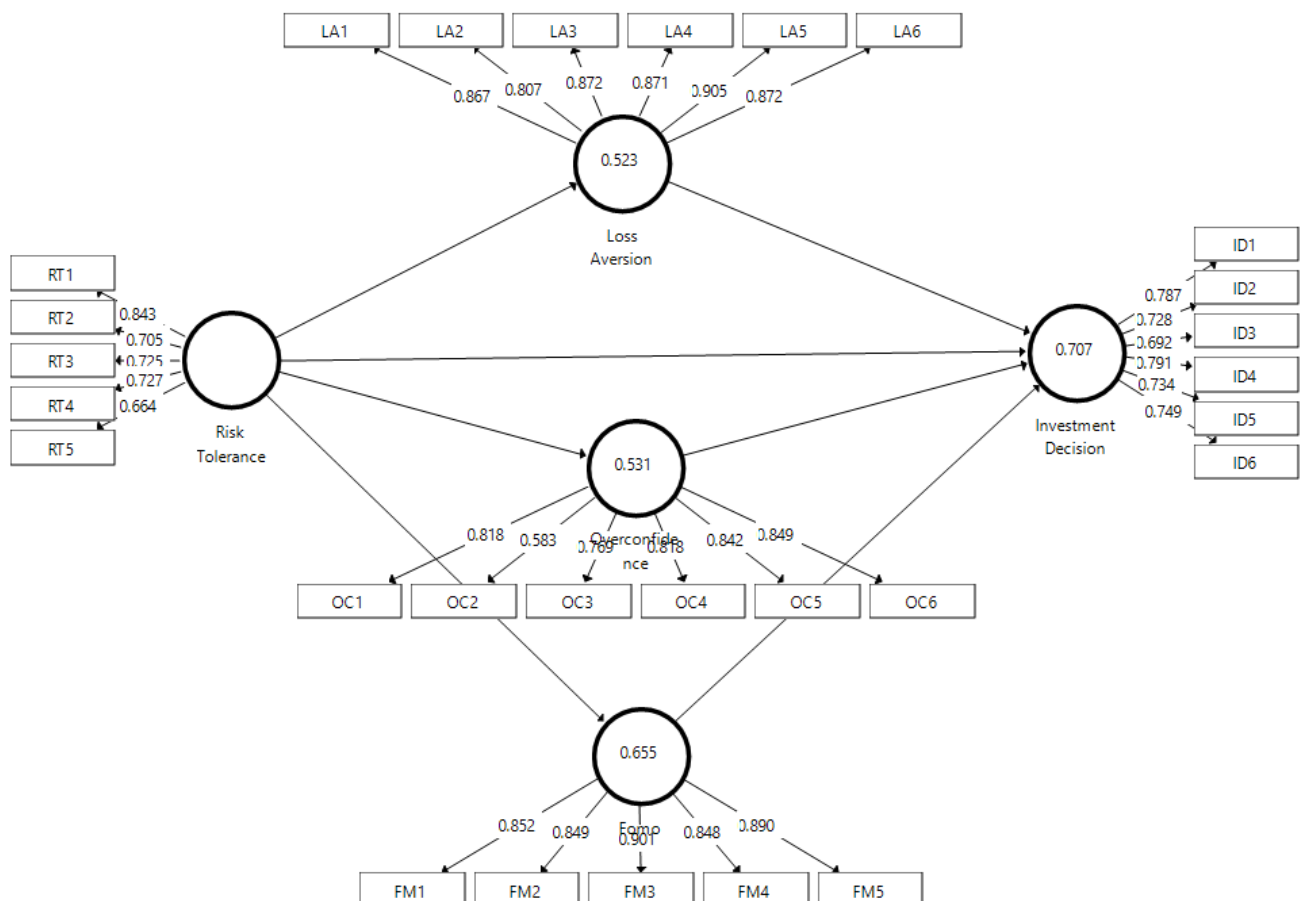


Figure 2. Initial Outer Model: PLS-SEM Path Diagram with Outer Loading Values (First Estimation, $n = 28$ Indicators)

Refined Outer Model Estimation (After Indicator Removal). Three indicators — RT5, OC2, and ID3 — were excluded from the measurement model on the grounds that their outer loadings fell below the 0.70 threshold prescribed by Hair et al. (2017), and their removal demonstrably enhanced overall model fit without undermining the content validity of the respective constructs. Following this refinement, Risk Tolerance was represented by four indicators (RT1, RT2, RT3, RT4), Overconfidence by five (OC1, OC3, OC4, OC5, OC6), and Investment Decisions by five (ID1, ID2, ID4, ID5, ID6). Loss Aversion (LA1–LA6) and FOMO (FM1–FM5) retained their originally specified indicator sets in full, as all loadings met the requisite threshold as visualized in Figure 3.

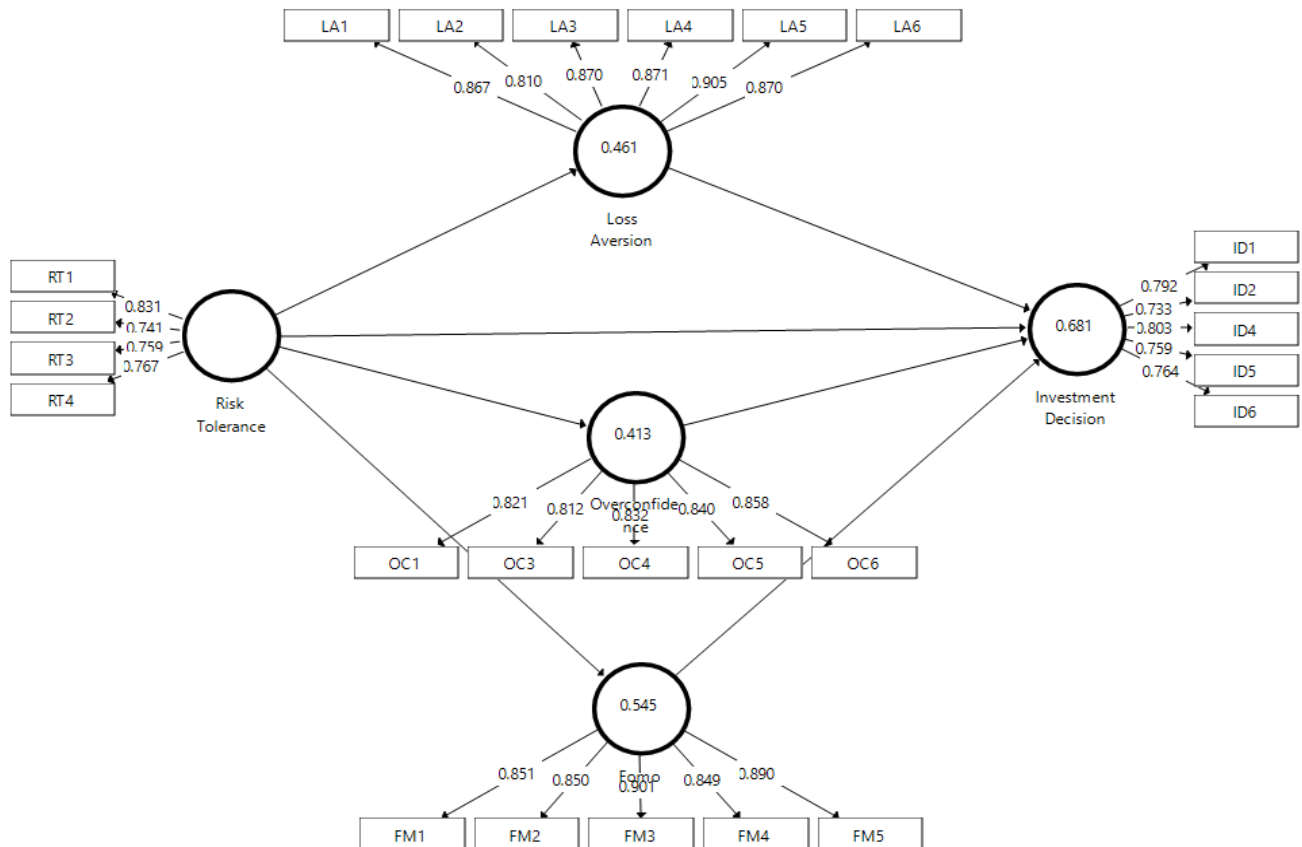


Figure 3. Refined Outer Model: PLS-SEM Path Diagram with Outer Loading Values (Post-Removal of RT5, OC2, ID3)

The second PLS-SEM estimation was conducted on the refined model of 25 indicators. As presented in Table 2, all 25 retained indicators achieved outer loading values above 0.70, ranging from 0.733 (ID2) to 0.905 (LA5). No further removal was required.

Table 2. Refined Outer Loadings — Second Estimation (After Removal, n = 25 Indicators)

Construct	Indicator 1	Indicator 2	Indicator 3	Indicator 4	Indicator 5	Indicator 6
Risk Tolerance	RT1 (0.831)	RT2 (0.741)	RT3 (0.759)	RT4 (0.767)	—	—
Loss Aversion	LA1 (0.867)	LA2 (0.810)	LA3 (0.870)	LA4 (0.871)	LA5 (0.905)	LA6 (0.870)
Overconfidence	OC1 (0.821)	OC3 (0.812)	OC4 (0.832)	OC5 (0.840)	OC6 (0.858)	—
FOMO	FM1 (0.851)	FM2 (0.850)	FM3 (0.901)	FM4 (0.849)	FM5 (0.890)	—
Investment Decision	ID1 (0.792)	ID2 (0.733)	ID4 (0.803)	ID5 (0.759)	ID6 (0.764)	—

Source: SmartPLS 4.0.

Construct Validity and Reliability. Following the confirmation of indicator reliability in the refined model, the assessment proceeded to evaluate internal consistency reliability and convergent validity for all five constructs. Internal consistency was assessed through Cronbach's alpha (α) and Composite Reliability (CR). Both are required to exceed 0.70, while CR should not exceed 0.95 to avoid indicator redundancy (Hair et al., 2017). As reported in Table 3, Cronbach's alpha values range from 0.778 (Risk Tolerance) to 0.933 (Loss Aversion) — all exceeding the 0.70 threshold. CR values range from 0.857 (Risk Tolerance) to 0.947 (Loss Aversion) — all within the acceptable 0.70–0.95 band. Internal consistency reliability is therefore confirmed for all five constructs. Convergent validity was assessed via the Average Variance Extracted (AVE), which must exceed 0.50 — indicating that the construct accounts for more than half the variance in its indicators (Fornell & Larcker, 1981). All five constructs satisfy this criterion: AVE values range from 0.594 (Investment Decision) to 0.754 (FOMO), confirming adequate convergent validity across the full model.

Table 3. Construct Reliability and Convergent Validity (Refined Model, n = 25 Indicators)

Construct	Cronbach's α	rho_A	CR	AVE	Status
Threshold	≥ 0.70	≥ 0.70	0.70–0.95	≥ 0.50	—
Risk Tolerance	0.778	0.784	0.857	0.601	Pass
Loss Aversion	0.933	0.934	0.947	0.750	Pass
Overconfidence	0.890	0.892	0.919	0.693	Pass
FOMO	0.918	0.919	0.939	0.754	Pass
Investment Decision	0.829	0.830	0.880	0.594	Pass

Note. α = Cronbach's Alpha; rho_A = Dijkstra-Henseler's rho; CR = Composite Reliability; AVE = Average Variance Extracted. All thresholds: $\alpha \geq 0.70$, CR 0.70–0.95, AVE ≥ 0.50 (Fornell & Larcker, 1981; Hair et al., 2017). Source: SmartPLS 4.0.

Inner Model Assessment (Structural Model). The inner model evaluates the explanatory power of the model, the significance and direction of the hypothesized paths, and the specific indirect (mediating) effects.

Coefficient of Determination (R^2 Adjusted). R^2 Adjusted values for all endogenous constructs are reported in Table 5, interpreted against Cohen's (1988) benchmarks of 0.25 (weak), 0.50 (moderate), and 0.75 (substantial). Investment Decision achieved an R^2 Adjusted of 0.671 — indicating that the model explains 67.1% of the variance in investment behavior, approaching the substantial threshold. FOMO yielded R^2 Adjusted = 0.542, indicating that Risk Tolerance explains 54.2% of variance in FOMO susceptibility. Loss Aversion (0.457) and Overconfidence (0.409) both approach the moderate benchmark. Collectively, these R^2 values confirm that dispositional risk tolerance holds strong explanatory power over all three mediating biases.

Table 5. Coefficient of Determination (R^2 and R^2 Adjusted)

Endogenous Construct	R^2	R^2 Adjusted	Interpretation
Loss Aversion	0.461	0.457	Moderate (approaching 0.50)
Overconfidence	0.413	0.409	Moderate (approaching 0.50)
FOMO	0.545	0.542	Moderate (approaching 0.50)
Investment Decision	0.681	0.671	Moderate–Substantial

Direct Effect. Path coefficients and their statistical significance were estimated through bias-corrected bootstrapping with 5,000 subsamples, following Hair et al. (2017). Direct effects were assessed for H1, while mediation hypotheses H2, H3, and H4 were evaluated through specific indirect effect analysis (Sarstedt et al., 2020). Significance is determined at $p < 0.05$, corresponding to a t-statistic greater than 1.65 (one-tailed).

Table 4. Direct Effect

Path	β	Mean	STDEV	T-Statistic	p-value	Decision
Risk Tolerance $\rightarrow$ Investment Decision	0.388	0.387	0.108	3.592	0.000	Supported

Note. β = original sample path coefficient; bootstrapping 5,000 subsamples; p-value one-tailed. Source: SmartPLS 4.0.

H1 is supported. The direct path from Risk Tolerance to Investment Decision yields $\beta = 0.388$, $t = 3.592$, $p < 0.001$ — a statistically robust positive effect that confirms the foundational premise of the dispositional mediation model. Investors with higher dispositional risk tolerance are significantly more likely to commit to investment decisions, independent of the three mediating biases. This finding aligns with the established literature demonstrating that FRT is a significant positive predictor of equity participation, trading frequency, and allocation to risky assets (Grable, 2000; Morningstar, 2022; Rawat, 2024). In the Indonesian retail investor context, this result is particularly meaningful: young investors who enter the capital market with a higher baseline tolerance for financial uncertainty are demonstrably more decisive in their investment behavior — a finding with direct implications for investor profiling practices under the OJK regulatory framework.

Indirect Effects. Hypotheses H2, H3, and H4 propose that loss aversion, overconfidence, and FOMO respectively mediate the relationship between dispositional risk tolerance and investment decisions. All three indirect effects were estimated simultaneously within the same PLS-SEM structural model. Results are summarized in Table 5 below, followed by individual hypothesis discussions.

Table 5. Specific Indirect Effects

Hypothesis & Path	β	Mean	STDEV	T-Statistic	p-value	Decision
H2: Risk Tolerance $\rightarrow$ Loss Aversion $\rightarrow$ Investment Decision	0.047	0.068	0.074	1.441	0.075	Not Supported
H3: Risk Tolerance $\rightarrow$ Overconfidence $\rightarrow$ Investment Decision	0.177	0.227	0.085	2.722	0.003	Supported
H4: Risk Tolerance $\rightarrow$ FOMO $\rightarrow$ Investment Decision	0.147	0.272	0.097	2.750	0.003	Supported

Source: SmartPLS 4.0.

This study tested a dispositional mediation model in which financial risk tolerance functions as a stable antecedent, with loss aversion, overconfidence, and FOMO serving as its situational transmission mechanisms toward investment decisions.

The mediation pathway through loss aversion is not supported ($\beta = 0.047$, $p = 0.075$). While risk tolerance significantly predicts loss aversion levels (a-path: $\beta = 0.679$, $p < 0.001$), loss aversion fails to significantly predict investment decisions (b-path: $\beta = 0.070$, $p = 0.218$), blocking the indirect effect. This is theoretically coherent rather than invalidating. High-tolerance investors do exhibit reduced loss aversion, but in this digitally-engaged, predominantly young Indonesian sample, that reduction does not translate into measurable investment activity. In a high-FOMO, social-media-driven environment, loss aversion's constraining influence appears overridden by social and momentum forces once stronger mediators are simultaneously active — consistent with (Rawat, 2024) finding that loss aversion's mediating role is most pronounced in low-risk-tolerance populations.

Overconfidence functions as a significant mediating channel ($\beta_{\text{indirect}} = 0.177$, $p = 0.003$), with both paths statistically significant (a-path: $\beta = 0.643$, $p < 0.001$; b-path: $\beta = 0.275$, $p = 0.007$). High-tolerance investors enter market contexts with a pre-existing motivational orientation toward engagement. In Indonesia's digital investment landscape — where Gen Z and millennial investors self-educate through financial influencers and social platforms — this orientation manifests as overconfident self-appraisal: the belief that one's analytical competence exceeds peers, that price movements are forecastable, and that past successes reflect skill rather than chance (Barber & Odean, 2001). This activated overconfidence then amplifies investment activity. Critically, the finding identifies the dispositional source: it is not overconfidence alone that drives decisions, but the risk-tolerant investor's propensity to express that tolerance through overconfident behavior within an information-rich market environment.

FOMO also functions as a significant mediating channel ($\beta_{\text{indirect}} = 0.147$, $p = 0.003$). The a-path from risk tolerance to FOMO is the strongest coefficient in the entire model ($\beta = 0.738$, $p < 0.001$), accounting for over 54% of variance in FOMO levels ($R^2_{\text{adj}} = 0.542$). Although the b-path is marginally non-significant ($\beta = 0.199$, $p = 0.059$), the full indirect effect is significant,

consistent with full mediation. In a digital environment where financial influencers, Stockbit communities, and WhatsApp investor groups continuously broadcast peer activity and trending signals, high-tolerance investors' appetitive market orientation is systematically channeled into FOMO — the psychological urgency to act before opportunities disappear.

FOMO emerges as a stronger mediating pathway than loss aversion, inverting classical Prospect Theory's predictions. Among Gen Z and millennial investors — for whom social comparison is embedded in daily digital interaction and loss-aversion thresholds are elevated by high dispositional risk tolerance — FOMO operates as a more immediate behavioral trigger than the longer-horizon, regret-based mechanism of loss aversion (Bo, 2023; Chi et al., 2025). Together, these results support the dispositional reframing of investor behavioral dynamics proposed in this study.

5. Conclusion

This study challenges the conventional assumption in behavioral finance that psychological biases independently determine risk tolerance as a situational outcome. Instead, drawing on Big Five Trait Theory, Prospect Theory, and the person–situation interactionist framework, it proposes that financial risk tolerance functions as a stable dispositional antecedent, with loss aversion, overconfidence, and FOMO serving as its situational transmission mechanisms.

Empirical results broadly support this reframing. Risk tolerance exerts a robust direct effect on investment decisions ($\beta = 0.388$, $p < 0.001$). Overconfidence and FOMO emerge as significant mediators, while loss aversion's pathway is not supported — a theoretically coherent finding given the sample's high-tolerance, digitally-engaged profile.

The study makes three contributions. First, it offers the first empirical test of a fully dispositional mediation model encompassing all three major behavioral biases simultaneously. Second, it demonstrates that in Indonesia's digital investment environment — marked by high FOMO pressure and a young, socially connected retail investor base — overconfidence and FOMO are the dominant transmission channels, while loss aversion is effectively neutralized. Third, it yields a practical framework: risk profiling should treat risk tolerance as the primary dispositional input, and behavioral interventions should target bias channels specific to each investor's dispositional profile rather than applying generic corrections.

Several limitations should be noted. The cross-sectional design prevents causal verification of the proposed dispositional ordering, making longitudinal or experimental follow-up essential. The parallel treatment of mediators also leaves untested the possibility of sequential effects — particularly an RT → Overconfidence → FOMO → ID cascade — which serial mediation models could better capture. Finally, the Indonesian context shapes these findings in ways that may not generalize: a rapidly growing market with a young, digitally-native investor base likely amplifies FOMO and overconfidence relative to loss aversion. Cross-national studies are needed to establish broader applicability.

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