

When Risk Tolerance Turns into Irrational Investment Choices: The Moderating Role of Trading Performance

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Abstract

Indonesia's capital market has expanded at a remarkable pace. By July 2025, the number of registered individual investor accounts (SIDs) had reached 17,016,329 an 11.42% increase from the 14,871,639 SIDs recorded at the close of 2024 yet national financial literacy still stands at only 65.43%. That gap between market participation and genuine financial understanding leaves many investors exposed to irrational investment behavior, including overtrading, herding, and the disposition effect. This study investigates how risk tolerance shapes irrational investment decisions among individual investors in Sumatera Utara, and whether trading performance moderates that relationship. Using a cross-sectional survey design and PLS-SEM analysis on active SID holders in the province (population approximately 592,876 as of May 2024), we recruited respondents through purposive sampling and confirmed adequate discriminant validity through HTMT values below 0.90. The results show that risk tolerance exerts a positive and significant direct effect on irrational investment decisions ($\beta = 0.369$; $t = 7.521$; $p < 0.001$), while trading performance does not significantly moderate this relationship ($\beta = 0.004$; $t = 0.118$; $p = 0.906$). With an R^2 of 0.674, the model demonstrates substantial predictive power. These findings reinforce risk tolerance as the dominant direct antecedent of irrational investment behavior and suggest that trading performance may be more productively examined as a mediating variable in future work. Practical implications extend to OJK, the Indonesia Stock Exchange (IDX), securities firms, and digital investment platforms, all of which stand to benefit from stronger risk profiling, behavioral-bias-oriented financial literacy programs, and behavioral nudge features tailored to young retail investors.

Keywords: risk tolerance, trading performance, irrational investment decision, behavioral finance, individual investors, Sumatera Utara

1. Introduction

Few developments in Indonesia's financial landscape over the past several years have been as striking as the rapid growth of its retail investor base. Data from the Financial Services Authority (OJK) show that the number of Single Investor Identification (SID) accounts reached 17,016,329 by July 2025 an 11.42% increase from the 14,871,639 SIDs recorded at the end of 2024. This expansion reflects multiple forces at once: improved digital access through mobile investment platforms, active market outreach campaigns, and growing public curiosity about personal finance, especially among younger Indonesians who came of age during a period of elevated economic uncertainty.

But participation in a market and informed participation in a market are not the same thing. The 2024 National Survey on Financial Literacy and Inclusion (SNLIK) reported Indonesia's national financial literacy index at 65.43%, alongside a financial inclusion index of 75.02%. The gap between those two figures matters. It means that a significant portion of investors enter the market capable of accessing investment products but without the conceptual tools to navigate them wisely. In practical terms, this environment is fertile ground for irrational investment behavior not as a rare anomaly, but as a common pattern.

There is additional context worth noting here. Bank Indonesia's December 2024 consumer survey recorded a Consumer Confidence Index of 127.7, which signals broad optimism about economic conditions. Yet the same survey found that 74.4% of household income continued to flow primarily toward short-term consumption. Optimism and investment readiness are not equivalent, and this tension shapes the behavioral backdrop against which individual investors make their decisions often under pressure, often without adequate information.

This is where behavioral finance proves its value. Unlike classical financial theory, which assumes investors act as rational utility-maximizers, behavioral finance starts from a more realistic premise: that cognitive and emotional factors reliably push investors away from optimal decisions. A 2024 World Economic Forum survey found that 36% of inactive retail investors cited fear of financial loss as a barrier to entry, while 54% felt they simply lacked sufficient investment knowledge. These are not informational gaps that better data alone can fix; they reflect deep-seated psychological tendencies. A 2025 McKinsey report observed similar dynamics globally, noting that even investors seeking stability are frequently buffeted by market sentiment and inflationary uncertainty a pattern especially visible in emerging markets, where information asymmetries and limited financial literacy tend to amplify herding and other behavioral biases.

Indonesia's own capital market provided a vivid illustration of this volatility during the 2024–2025 period. The Composite Stock Price Index (IHSG) closed 2024 at 7,079.905, dropped to 5,967.988 in April 2025, then recovered to 7,175.819 by May 2025. For investors particularly members of Generation Z, who account for much of the recent SID growth navigating that kind of turbulence without solid analytical footing is genuinely difficult. The temptation to react emotionally, to follow the crowd, or to chase short-term gains is real, and the evidence suggests that many investors do exactly that.

Against this backdrop, risk tolerance occupies a central position in behavioral finance research on investor decision-making. Broadly understood as an individual's willingness to accept uncertainty in pursuit of higher returns, risk tolerance has long been studied as a driver of asset allocation and market participation. High risk tolerance can enable productive engagement with markets but it can also tip into excessive risk-taking and the kinds of irrational decisions that erode wealth rather than build it. Meanwhile, trading performance the actual outcomes investors experience from their trading activities is theoretically capable of shaping subsequent behavior. Successful trading can reinforce confidence, sometimes to the point of overconfidence; poor performance can induce caution or, in some cases, trigger impulsive attempts to recover losses.

Both pathways suggest that trading performance could moderate the link between risk tolerance and irrational behavior. Testing that moderation hypothesis is one of this study's central aims.

2. Literature Review

2.1 Risk Tolerance

Risk tolerance the degree to which an individual willingly accepts uncertainty and potential losses in exchange for higher expected returns has been foundational to financial planning and investment research since at least Grable and Lytton's (1999) early work on its measurement. In classical portfolio theory, Markowitz (1952) treated risk tolerance as a key determinant of optimal asset allocation; in behavioral finance, scholars such as Barberis and Thaler (2003) recognized it as something more dynamic shaped by personality, past experiences, and social context rather than fixed by rational calculation.

Empirically, investors with higher risk tolerance tend to hold larger allocations in equities and other volatile instruments, while those with lower tolerance favor deposits or government bonds (Hallahan, Faff, & McKenzie, 2004; Dorn & Sengmueller, 2009). More interesting, perhaps, is the finding that high risk tolerance can also serve as a gateway to behavioral excess: rather than enabling calculated risk-taking, it can make investors susceptible to sensation-seeking, overtrading, and speculative decisions that undermine long-term returns.

In the Indonesian context, this pattern appears in several studies. Hendarto, Anastasia, and Basana (2021) found that financial risk tolerance significantly and positively predicted stock investment decisions among Indonesian millennial investors. Adiputra (2021), Aprilia and Hartono (2023), and Yundari and Artati (2024) each documented risk tolerance as a mediating variable linking cognitive biases—overconfidence, representativeness, herding to actual investment choices. Taken together, these studies position risk tolerance not merely as a moderating background factor but as an active channel through which psychological tendencies translate into market behavior.

2.2 Trading Performance

Trading performance broadly defined as the realized returns and risk-adjusted outcomes of an investor's trading activity over time (Sharpe, 1966; Magdon-Ismail & Atiya, 2004) occupies a somewhat paradoxical place in behavioral finance. On one hand, frequent trading is generally associated with worse net returns: Barber and Odean (2000) demonstrated this compellingly, attributing the gap largely to transaction costs and poor market timing. On the other hand, the subjective experience of past performance whether an investor felt successful or not shapes future behavior in ways only loosely connected to objective outcomes.

The mechanism is well-established. Investors who experience a run of profitable trades often attribute their success to personal skill rather than favorable market conditions, which increases confidence and trading frequency (Gervais & Odean, 2001; Choi, Laibson, Madrian, & Metrick, 2009). Those who do poorly may become more cautious, or, in some cases, more impulsive particularly when loss aversion and the desire to recover losses take hold (Seru, Shumway, & Stoffman, 2010). In either case, trading performance does not merely summarize the past; it

feeds forward into subsequent decisions, which is precisely what makes it a theoretically plausible moderator of the relationship between risk tolerance and irrationality.

In this study, trading performance is operationalized as a moderating variable: we are interested in whether past performance whether strong or weak amplifies or dampens the connection between an investor's risk tolerance and their tendency toward irrational decisions, such as chasing past winners, overreacting to short-term gains, or doubling down on losing positions (Shefrin & Statman, 1985; Baker, Kumar, Goyal, & Gaur, 2019).

2.3 Irrational Investment Decisions

What behavioral finance calls irrational investment decisions are not simply mistakes they are systematic, predictable deviations from normative standards such as Expected Utility Theory (von Neumann & Morgenstern, 1944) and Mean-Variance Optimization (Markowitz, 1952), arising from identifiable psychological mechanisms (Kahneman & Tversky, 1979; Barberis & Thaler, 2003). Examples include excessive trading without informational advantage (Barber & Odean, 2000), following rumors or social media tips without verifying fundamentals (Bikhchandani & Sharma, 2001; Rahayu, Putra, Oktaverina, & Ningtyas, 2021), concentrating investments in speculative assets rather than diversifying, and holding losing positions to avoid realizing losses the disposition effect described by Shefrin and Statman (1985).

Recent empirical work in Indonesia and other emerging markets reinforces how prevalent these patterns are. Wibowo, Indrawati, and Aisjah (2023) and Kaban (2024) both found that herding and overconfidence biases significantly reduce decision quality among Indonesian retail investors, while Rahayu et al. (2021) and Yusbardini and Natsir (2022) documented high levels of speculative trading and misaligned risk exposure among similar populations. These studies also point to a key nuance: financial education can either mitigate or reinforce these tendencies, depending on the quality of information and the behavioral framing involved (Hendarto et al., 2021; Van Rooij, Lusardi, & Alessie, 2011).

3. Research Method

3.1 Research Design

This study adopts a quantitative, explanatory research design using a cross-sectional survey of individual investors in Sumatera Utara. The explanatory approach is appropriate because our central goal is to test theoretically derived causal relationships specifically, how risk tolerance affects irrational investment decisions and whether trading performance moderates that effect (Creswell & Creswell, 2018; Sekaran & Bougie, 2016). The cross-sectional format, in which all constructs are measured at a single point in time, is consistent with prior behavioral finance studies that examine investor psychology and decision behavior simultaneously (Hair, Hult, Ringle, & Sarstedt, 2022).

Data are analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is well-suited for studies of this kind particularly those involving latent variables, prediction-oriented objectives, and data that cannot be assumed to follow a normal distribution. PLS-SEM also allows robust moderation testing through the product indicator approach, which is the

method applied here (Henseler, Ringle, & Sarstedt, 2015; Hair et al., 2022; Sarstedt, Ringle, & Hair, 2021).

3.2 Population, Sample, and Sampling Technique

The study population consists of individual investors in Sumatera Utara who hold an active Single Investor Identification (SID) and have engaged in capital market transactions whether in stocks, mutual funds, or bonds through a securities company or digital investment platform within the past twelve months. According to Otoritas Jasa Keuangan (OJK) Sumatera Utara, the total number of SIDs in the province reached approximately 592,876 as of May 2024, reflecting a large and rapidly growing investor base (OJK Sumut, 2024; Kustodian Sentral Efek Indonesia, 2024).

A target sample of several hundred respondents was set, consistent with recommendations for SEM-based studies of this type (Hair et al., 2022; Kock & Hadaya, 2018; Adiputra, 2021). Respondents were selected through non-probability purposive sampling (Sekaran & Bougie, 2016; Etikan, Musa, & Alkassim, 2016), with three eligibility criteria: (1) residing in Sumatera Utara, (2) holding an active SID, and (3) having completed at least one capital market transaction in the preceding twelve months. Data were gathered via an online questionnaire distributed through investment communities, campus investment galleries, securities company networks, and social media groups focused on investment topics in Sumatera Utara.

3.3 Types of Data, Sources, and Availability

Primary data come from cross-sectional survey responses, collected directly from individual investors using multi-item Likert-type scales for each construct. Survey-based measurement is appropriate here because the constructs of interest especially risk tolerance are inherently subjective and latent; they cannot be directly observed from trading records or financial statements alone (Grable & Lytton, 1999; Barberis & Thaler, 2003).

Secondary data were used for contextual grounding: official statistics and press releases from KSEI, IDX, and OJK on investor numbers and demographic profiles (Otoritas Jasa Keuangan, 2025; Kustodian Sentral Efek Indonesia, 2024; Bursa Efek Indonesia, 2025), as well as peer-reviewed literature on behavioral finance, financial socialization, and investor behavior used to develop the theoretical framework and measurement instruments (Barberis & Thaler, 2003; Hendarto et al., 2021; World Economic Forum, 2024).

3.4 Operational Definition and Measurement of Variables

All constructs are treated as latent variables with multiple reflective indicators, measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5) (Likert, 1932; Hair et al., 2022). Measurement items were adapted from existing validated scales and contextualized to the Indonesian capital market setting through wording adjustments and expert consultation with academics and practitioners in finance and investment education (Lawshe, 1975; Hendarto et al., 2021).

Risk tolerance (X) is operationally defined as an investor's willingness to accept uncertainty

and the possibility of financial loss in pursuit of higher expected returns. Items were adapted from the Grable Lytton Financial Risk Tolerance Scale (Grable & Lytton, 1999; Grable, 2000) and cover preference for high-risk, high-return investments; comfort with short-term portfolio fluctuations; willingness to invest in equities over safer alternatives such as deposits; and acceptance of the possibility of short-term losses for long-term gain (Hallahan et al., 2004; Van Rooij, Lusardi, & Alessie, 2011; Dorn & Sengmueller, 2009).

Trading performance (M) is defined as the investor's self-reported evaluation of recent trading outcomes, including realized profits, success rate of trades, and satisfaction with portfolio returns relative to expectations and benchmarks. Indicators reflect perceived profitability, self-rated performance against the IHSG, overall return satisfaction, and perceptions of trading skill relative to other investors (Barber & Odean, 2000, 2001; Gervais & Odean, 2001; Seru, Shumway, & Stoffman, 2010).

Irrational investment decisions (Y) captures systematic behavioral deviations from rational decision norms. Indicators cover the tendency to buy or sell based on unverified rumors or tips; engaging in frequent short-term trading to chase quick profits; holding onto losing stocks to avoid realizing losses; concentrating capital in a small number of speculative assets; and disregarding fundamental analysis when making investment choices (Kahneman & Tversky, 1979; Shefrin & Statman, 1985; Bikhchandani & Sharma, 2001; Pompian, 2012; Ahmad, 2024). Construct validity and reliability for all three variables are evaluated empirically through confirmatory factor analysis within the PLS-SEM framework (Fornell & Larcker, 1981; Henseler et al., 2015; Hair et al., 2022).

3.5 Data Analysis Technique

Analysis proceeded in two stages. First, descriptive statistics were used to characterize respondents and summarize behavioral tendencies among investors in Sumatera Utara (Sekaran & Bougie, 2016). Second, the PLS-SEM measurement (outer) model was evaluated for indicator reliability (outer loadings ≥ 0.70), internal consistency (Cronbach's α and composite reliability ≥ 0.70), convergent validity (AVE ≥ 0.50), and discriminant validity via the Fornell–Larcker criterion and HTMT ratios below 0.90 (Cronbach, 1951; Fornell & Larcker, 1981; Henseler et al., 2015; Hair et al., 2022). Bootstrapping with 5,000 resamples was then applied to estimate path coefficients, standard errors, t-statistics, and p-values for both the direct effects and the moderation hypothesis, using SmartPLS 4's product indicator approach combined with a two-stage estimation procedure (Henseler et al., 2015; Hair et al., 2022; Sarstedt et al., 2021).

4. Finding and Discussion

Measurement Model. Reliable and valid construct measurement is a prerequisite for drawing meaningful inferences from structural results. Following Sarstedt et al. (2014) and Leguina (2015), we evaluated composite reliability, convergent validity (AVE), and discriminant validity for all three constructs. Table 1 presents the full results, and Figure 1 displays the corresponding measurement model.

Table 1. Reliability & Validity

Construct	Item	Loading Factor	AVE	CR	CA
Risk Tolerance	RT1	0.957	0.907	0.987	0.985
	RT2	0.939			
	RT3	0.962			
	RT4	0.949			
	RT5	0.956			
	RT6	0.947			
	RT7	0.945			
	RT8	0.961			
	RT9	0.957			
Trading Performance	TP1	0.970	0.943	0.988	0.985
	TP2	0.972			
	TP3	0.975			
	TP4	0.963			
	TP5	0.976			
Irrational Investment Decision	IID1	0.919	0.865	0.983	0.980
	IID2	0.924			
	IID3	0.925			
	IID4	0.924			
	IID5	0.934			
	IID6	0.931			
	IID7	0.926			
	IID8	0.953			
	IID9	0.933			

As Table 1 shows, all individual factor loadings exceed the recommended threshold of 0.70

(Hair et al., 2019), and AVE values for each construct surpass the 0.50 benchmark (Hair et al., 2021), confirming adequate convergent validity. Composite reliability and Cronbach's alpha are also well above the 0.70 threshold across all constructs. These results provide a solid measurement foundation for the structural analysis that follows.

Discriminant Validity (HTMT). Discriminant validity was assessed using the Heterotrait–Monotrait Ratio of Correlations (HTMT) criterion developed by Henseler, Ringle, and Sarstedt (2015). Table 2 presents the HTMT matrix.

Table 2. HTMT

	Risk Tolerance	Trading Performance	Irrational Inv. Decision
Risk Tolerance			
Trading Performance	0.801		
Irrational Investment Decision	0.775	0.803	

All HTMT values fall below the conservative 0.90 threshold, with the highest value being 0.803 (between Trading Performance and Irrational Investment Decision). This confirms that the three latent constructs are empirically distinct from one another—a necessary condition for interpreting structural relationships with confidence (Henseler et al., 2015; Hair et al., 2022).

Evaluation of the Structural Model (Inner Model). The structural model was estimated using bootstrapping with 5,000 resamples. A relationship is considered statistically significant when $t \geq 1.96$ and $p < 0.05$ (two-tailed) (Henseler et al., 2015). Table 3 presents the path coefficients and significance test results.

Table 3. Significance Impact Test

	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics (O/STDEV)	P Values
Direct Effect					
Risk Tolerance → Irrational Investment Decision	0.369	0.368	0.049	7.521	0.000
Moderating Effect					
Moderating Effect 1 → Irrational Investment Decision	0.004	0.004	0.037	0.118	0.906

Of the two hypothesized relationships, one was strongly supported and one was not. The direct effect of risk tolerance on irrational investment decisions was positive and significant ($\beta = 0.369$; $t = 7.521$; $p = 0.000$), confirming that investors with higher risk tolerance show a greater tendency toward irrational behavior. The moderation effect, by contrast, was negligible and statistically insignificant ($\beta = 0.004$; $t = 0.118$; $p = 0.906$): trading performance did not meaningfully strengthen or weaken the risk tolerance–irrationality link in this sample.

Table 4. R Square

	R Square	R Square Adjusted
Irrational Investment Decision	0.674	0.670

The R^2 value of 0.674 (R^2 adjusted = 0.670) indicates that 67.4% of the variance in irrational investment decisions is explained by the variables in the model—a level classified as substantial by Chin (1998) and Hair et al. (2022). The model thus demonstrates strong predictive validity overall, even though the moderation hypothesis was not supported.

The Effect of Risk Tolerance on Irrational Investment Decisions. The finding that risk tolerance significantly and positively predicts irrational investment decisions ($\beta = 0.369$; $t = 7.521$; $p < 0.001$) is perhaps the study’s most actionable result. H1 is accepted: higher risk tolerance among individual investors in Sumatera Utara is associated with a greater tendency to make investment decisions that deviate from rational principles including overtrading, herding, panic selling, and purchasing speculative assets without fundamental analysis. This is consistent with a well-established body of behavioral finance research. Dorn and Sengmueller (2009) and Grinblatt and Keloharju (2009) both found that higher risk tolerance correlates with sensation-seeking and excessive trading frequency, which tends to reduce rather than improve investment outcomes. Barber and Odean (2000) showed that the most active individual traders earn the lowest net returns, and much of that activity appears driven by high risk appetite rather than genuine informational advantage. In emerging market settings, Ahmad (2024) documented similar patterns: excessive risk tolerance is associated with speculative decisions and a tendency to bypass fundamental analysis. In Indonesia specifically, Hendarto et al. (2021) showed that financial risk tolerance significantly predicts stock investment behavior among millennial investors, while Adiputra (2021), Aprilia and Hartono (2023), and Yundari and Artati (2024) each traced the central role of risk tolerance in linking cognitive biases to actual investment choices. Our findings extend this body of work by treating irrational investment decisions as the primary dependent variable and demonstrating that risk tolerance is a strong independent predictor—not merely a mediator or background variable. The practical implication is important. In an environment characterized by rapid investor growth and relatively low financial literacy, risk tolerance does not simply enable productive market participation; it can actively drive irrational behavior. This points to the need for risk profiling tools that go beyond labeling investors as “conservative” or “aggressive” and instead help individuals recognize the specific behavioral tendencies that accompany different levels of risk appetite.

The Role of Trading Performance as a Moderator (H2). The moderation hypothesis did not receive empirical support. The interaction term between risk tolerance and trading performance produced a coefficient of $\beta = 0.004$ ($t = 0.118$; $p = 0.906$) essentially indistinguishable from zero. Whether an investor's recent trading performance was strong or weak, their level of risk tolerance predicted irrational behavior to roughly the same degree. H2 is not supported by the data. Several interpretations are worth considering here. The most straightforward is that behavioral biases are simply more persistent than feedback-based learning models would predict. Statman (2019) and Pompian (2012) have both argued that cognitive and emotional biases do not self-correct easily, even when investors have access to outcome information. The high-risk-tolerance investor who suffered losses last quarter does not necessarily become more cautious next quarter; the underlying psychological mechanisms that drive the behavior are not easily overridden by performance data alone. This interpretation is reinforced by findings on self-attribution bias and reinforcement learning (Gervais & Odean, 2001; Choi et al., 2009): investors tend to attribute gains to personal skill and losses to bad luck or external conditions, which means performance feedback gets filtered in ways that protect established behavioral tendencies rather than revising them. From that angle, trading performance's failure to moderate risk tolerance's effect is less surprising than it might initially appear. There are also methodological considerations worth noting. Trading performance in this study was measured through self-report, which introduces the possibility of common method bias—particularly given that investors with high risk tolerance may tend to evaluate their own performance more favorably than objective records would support (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Additionally, the cross-sectional design cannot capture the dynamic feedback loop between performance and behavior that develops over multiple trading cycles (Gervais & Odean, 2001). Many respondents in Sumatera Utara appear to have entered the market during the 2020–2024 period (OJK Sumut, 2024; KSEI, 2024), and their relatively limited experience may not yet have produced the differentiated performance histories needed to generate meaningful moderation effects. Finally, a theoretical question remains open for future research: whether trading performance is more appropriately positioned as a mediator rather than a moderator in this kind of model. Several previous studies have found that performance outcomes mediate the relationship between investor psychological characteristics and subsequent decisions (Seru, Shumway, & Stoffman, 2010; Barber, Lee, Liu, & Odean, 2009), which would explain why moderation testing did not yield significant results here.

5. Conclusion

This study set out to examine two questions: whether risk tolerance directly predicts irrational investment decisions among individual investors in Sumatera Utara, and whether trading performance moderates that relationship. The evidence on the first question is clear and strong: risk tolerance is a significant, positive predictor of irrational behavior, with a path coefficient of $\beta = 0.369$ and a model R^2 of 0.674. The evidence on the second question is equally clear, though in the opposite direction: trading performance does not meaningfully moderate the relationship in this sample, and H2 is not supported.

These findings reinforce the position of risk tolerance as the dominant direct antecedent of

irrational investment behavior in Indonesia's retail investor population, while also expanding the behavioral finance literature in Indonesia beyond its previous focus on cognitive bias dimensions. The insignificance of the moderation effect suggests that trading performance may be more productively examined as a mediator variable in the causal pathway between investor psychology and investment decisions, ideally with a longitudinal design that can capture how the feedback loop between performance and behavior evolves over time.

For practical stakeholders, the implications are several. OJK and IDX should consider developing risk profiling instruments that are more dynamic and behaviorally oriented not just matching investors with products, but helping them understand the biases their risk appetite may produce. Financial literacy programs that focus on behavioral bias recognition and management are likely to be more effective than general financial knowledge campaigns, particularly given the national literacy index of 65.43% and the continuing dominance of young, less experienced investors in the market. Securities firms and digital investment platforms, meanwhile, are well-positioned to develop behavioral nudge features: automatic alerts against overtrading patterns, portfolio simulations that make irrational tendencies visible, and educational content tailored to the biases most common among retail investors. For Generation Z investors in Sumatera Utara who have driven much of the SID growth since 2020 these kinds of targeted interventions could make a meaningful difference.

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