Effects of Behavioural Biases on Investment Decisions: A Systematic and Meta-Analysis

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ABSTRACT

Traditional finance theories assume that investors behave rationally and make decisions based on complete information. However, empirical evidence indicates that investors are often influenced by behavioural biases that lead to deviations from rational decision-making. To get more insights on this phenomenon, the study investigated the effects of between behavioural biases and investment decisions by synthesising global empirical findings through a systematic and meta-analysis protocol (PRISMA-P). Using a set of inclusion and exclusion criterion, sixty-four studies were identified. The results revealed that in all studies, hindsight bias has a significant positive effect on investment decisions. It implies that investors who increase the perceived predictability of past events are likely to make better investment decisions. On the other hand, the disposition effect and mental accounting bias have shown a significant negative effect on investment decision, implying that the presence of mental accounting and the disposition effect makes investors to make unfavourable decisions. Overconfidence, herding, availability, anchoring, loss aversion, and risk aversion are statistically insignificant, implying limited explanatory power to influence investment decisions. The study further found no publication bias given the insignificant intercept of Egger regression. The Egger regression further demonstrated that hindsight bias has significant positive effect on effect sizes, indicating the presence of systematic moderator effect. Biases such as overconfidence, anchoring, herding, representative, disposition effect, availability, mental accounting, risk aversion, and regret aversion are statistically insignificant, indicating the absence of systematic moderator effect. The study concluded that investor behaviour cannot be fully explained by rational models, behavioural economics models play a pivotal role in explaining investor patterns. The study's implications extend to policymakers, financial advisors, and investors, emphasising the importance of behavioural awareness and financial education in improving decision making.

KEYWORDS: *behavioural biases, investment decisions, meta-analysis, systematic review*

JEL CLASSIFICATION: *G11, D91*

1. INTRODUCTION

For years, investors have used the traditional financial models such as the Capital Structure Model, Capital Asset Pricing model established by (Sharpe 1964), (Lintner 1965, Mossin 1966), and the Efficient Market Hypothesis by (Fama, 1970) to evaluate their investment decisions (Brusov, 2023). These models are grounded in the assumption that individuals behave rationally. Despite their continued use, investors often experience significant financial losses. This reveals that traditional theories have limitations in explaining actual investment behaviour. In the early 1980s, a ground-breaking shift occurred in financial research with the emergence of behavioural finance, a field that integrates psychological insights into economic and financial decision making. Earlier works by Tversky and Kahneman (1971) had already questioned

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human rationality in judgment under uncertainty, laying the foundation for what would become a new field of study in finance. Behavioural finance emerged in response to increasing evidence that investor decisions are often influenced by emotions, beliefs, and cognitive limitations, rather than by objective information alone.

A key contribution to the field is the Prospect Theory, developed by Kahneman and Tversky (1979), which explains how investors evaluate potential gains and losses. According to this theory, individuals are risk averse when facing gains and risk seeking when confronting losses, leading to decision-making biases such as loss aversion and risk aversion (Charles, 2016, Madaan and Singh, 2019 and Zafar et al., 2024). Behavioural finance argues that these psychological deviations cause investors to make irrational decisions, often unconsciously, as stated by Abideen et al. (2023) and Pradhan (2021). These biases diverge sharply from assumptions embedded in traditional finance theories, which presume that markets are composed of rational agents acting on all available information. Instead, behavioural finance emphasises the investors are emotional, imperfect, and influenced by mental shortcuts (Schneider & Nunez, 2024). Biases in decision making are broadly categorised as either emotional or cognitive. Emotional biases stem from feelings or psychological discomfort and include traits such as loss aversion and regret aversion (Kumar & Chaurasia, 2024). Cognitive biases, on the other hand, are errors in reasoning, such as overconfidence, anchoring, and herding behaviour. These biases manifest consistently in financial decisions and often lead to sub-optimal outcomes, as evidenced by real-world anomalies such as market bubbles and crashes (Annu, 2024). Other behavioural theories include the bounded rationality by Herbert Simon (1990) which recognises that investors have cognitive limitations, and the theory of planned behaviour which recognises that one's behaviour is influenced by their intention.

Behavioural finance does not only critique traditional models, but offers a more realistic approach through which to view investor behaviour, recognising that psychology and environment significantly affect financial choices (Schneider & Nunez, 2024). Several empirical studies have shown that behavioural biases influence investment behaviour across diverse demographics and geographies; for instance, investor decisions have been found to be heavily context driven and influenced by factors such as overconfidence and herding bias (Prosad, 2015). These biases often interact, exacerbating irrational behaviour and complicating financial planning and policy development. Empirical evidence continues to demonstrate that psychological factors, such as overconfidence, have a significant impact on investment choices. Overconfidence has been linked to excessive investment and poor asset allocation decisions (Jiang & Tornikoski, 2019). Similarly, Lucchesi (2015) showed that Brazilian equity fund managers display the disposition effect, driven by behavioural tendencies such as herding and loss aversion. Njenga (2018) has also affirmed that regret aversion and anchoring affect investment in real estate and the equity markets.

Behavioural patterns such as holding onto losing investments for too long and prematurely selling winners adversely impact portfolio performance (Aspara and Hoffmann, 2015; Rehan, 2017; Gurung et al., 2024). These outcomes further support the argument that investors often act irrationally, especially when confronted with uncertainty or incomplete information. As such, traditional finance theories fall short in explaining observed investor behaviour (Rehan, 2017). As global financial markets grow increasingly complex, understanding behavioural biases has become critical for both individual and institutional investors. The rapid adoption of financial technologies, online trading platforms, and algorithmic models has made investment decisions more accessible, yet more prone to irrational influences. Social media, peer influence, and information overload have intensified biases such as herding and confirmation bias, as well

as the framing effect. Thus, the study seeks to explore the extent to which behavioural biases have influenced investment decision.

2. LITERATURE REVIEW

The study is based on the theoretical premises that describe the main theories which predict investor behaviour and develop a framework in which investment choices and mental biases can be evaluated. Theories such as the Prospect Theory by Kahneman and Tversky (1979) and the theory of Planned Behaviour. The study further reviewed empirical literature on behavioural biases and their influence on investment decision-making. Key cognitive and emotional biases that were examined in past studies consistently demonstrating their pervasive impact across different markets and investor groups. The theoretical framework is presented as in the forthcoming sections.

2.1.1 Prospect Theory

Prospect theory was formally developed by Kahneman and Tversky (1979) to explain how individuals make decisions under risk by evaluating outcomes relative to a reference point, rather than in terms of final wealth as assumed in expected utility theory. They demonstrated that individuals exhibit loss aversion, meaning that losses are felt more strongly than equivalent gains, and modelled this using a value function that is concave for gains and convex for losses. In the context of investor decisions, this insight explains why investors are reluctant to realise losses and instead hold on to underperforming assets, while quickly selling assets that have generated gains. This behavioural pattern, later termed the disposition effect by Shefrin and Statman (1985), reflects the central role of loss aversion and reference dependence in shaping investor behaviour.

In addition, Kahneman and Tversky (1979) showed that individuals display asymmetric risk preferences, being risk-averse when choices are framed as gains and risk-seeking when framed as losses. Kahneman and Tversky (1979) also introduced the concept of probability weighting, whereby decision-makers overweight small probabilities and underweight large ones. Building on these foundations, behavioural finance scholars such as Barberis, Shleifer and Vishny (1998) and Barberis and Thaler (2003) linked these psychological biases to observable investor behaviour, including excessive trading, overreaction to market information, and speculative investment choices. Together, these contributions clarify how the key aspects of prospect theory directly underpin behavioural biases that systematically influence investor decision-making.

2.1.2 The Theory of Planned Behaviour (Tpb)

The theory is built upon Ajzen's theory of reasoned action (Jiang & Tornikoski, 2019), where behaviour is guided by the intentions behind it and these can be affected by ones' attitude, their personal evaluation, including views, beliefs and values that were acquired through influences or public media attention (Jamshidi, 2024). Another component is perceived behavioural control which encompasses self-efficacy, that is, confidence in oneself to carry out an action successfully, resource availability which access whether one has what they need for the task to be completed. Subjective norms are also significant in influencing investors' decisions, particularly for those with limited financial knowledge who often depend on the advice of close family and friends. Individuals are inclined to heed the opinions of those they consider important. Another component is attitude toward the behaviour; it is the degree by which a person has a favourable or unfavourable evaluation of the expectation with respect to the behaviour of interest, and this intention will cause individuals to perform the intended behaviour

actions. Croy (2012), Shahriar Ferdous and Polonsky (2013); Koropp (2014); Quang (2023) have explored the impact of these norms on financial investment.

2.2 Empirical Review

Empirical evidence from diverse markets consistently demonstrates that behavioural biases exert a strong influence on investment decision-making. Charles and Kasilingam (2016) concluded that emotional factors are deeply intertwined with cognitive processes, finding a positive relationship between emotions and heuristics and between emotions and gambling, while also identifying an oppositive relationship between emotions and framing, suggesting that investor sentiment can simultaneously amplify intuitive decision-making and distort information processing. Similarly, Pradhan (2021) concluded that behavioural biases significantly shape asset allocation, showing that biases systematically affect individual investors' portfolio choices. In the Nigerian context, Aigbovo and Ilaboya found that loss aversion influences individual investment decisions, while overconfidence and self-attribution were less important, highlighting that fear of losses dominates confidence-driven behaviour in some developing markets.

A large body of studies identifies overconfidence bias as one of the most pervasive drivers of irrational investment behaviour. Metwally (2023) concluded that overconfidence distorts the rationality of individual investors' decisions, with information acquisition moderating its effect. Consistent with this, Kuranchie-Pong and Forson (2022) showed that overconfidence during the COVID-19 period led to overreaction to private information and underreaction to public information on the Ghana Stock Exchange. Sectoral evidence from Musah et al. (2024) further confirms that overconfidence is prevalent in the distribution, manufacturing, and agriculture sectors, contributing to excessive trading volumes.

Herding behaviour emerges as another dominant theme, particularly under conditions of uncertainty. Poshakwale and Mandal (2014) identified significant herding behaviour in the Indian stock market, especially during bear markets. However, contradictory evidence also exists. Gurung (2024) found that herding behaviour showed no significant relationship with investment choices among Nepalese investors, while Njenga (2018) similarly reported that herding had an insignificant relationship with real estate prices in Kenya. These mixed findings suggest that herding is highly sensitive to market structure, investor sophistication, and prevailing economic conditions.

Loss aversion and disposition-related biases are consistently documented across both individual and institutional settings, reinforcing predictions from prospect theory. At the professional level, Lucchesi et al. (2015) found that Brazilian equity fund managers exhibit the disposition effect, confirming that even sophisticated investors are prone to selling winners too early and holding onto losing positions. Extending this analysis, Arora and Rajendran (2023) concluded that the disposition effect is more pronounced in volatile markets and that investors affected by it tend to have lower portfolio performance, demonstrating the long-term costs of biased trading behaviour.

Cognitive biases such as anchoring, heuristics, and information-processing distortions further explain deviations from rational investment models. Fernández et al. (2011) concluded that high levels of information uncertainty favour herding behaviour, regardless of individual cognitive differences. Xie, Feng, and Gao (2022) found that retail investors demonstrate a stronger anchoring bias compared to institutional investors and that anchoring negatively correlates with one-month-ahead stock returns. Evidence from emerging markets supports these findings;

Nyangi (2018) concluded that stereotyping and overconfidence significantly affect investment decisions, and that increasing herding and stereotyping reduces investment value.

Studies also emphasise the role of financial literacy, experience, and technological interventions in moderating behavioural biases. Haag et al. (2024) provided evidence that artificial intelligence can mitigate the negative effects of anchoring bias, highlighting the potential of decision-support systems. Similarly, Wesslen and Karduni (2021) demonstrated that uncertainty visualisations can mitigate myopic loss aversion, improving long-term investment outcomes. These findings indicate that, while behavioural biases are persistent, their adverse effects can be reduced through structured decision frameworks and behavioural-aware policy interventions.

3. METHODOLOGY

The study used meta-analytic estimates to statistically combine the results obtained from the selected empirical studies. Contrary to narrative review approaches using solely descriptive comparisons, the analysis translates findings of individual studies into standardised effect size measures and provides a uniform control for a comprehensive overview of the aggregated effects of behavioural biases on investment decision making. Firstly, the study estimated the effect size as a measure of the scale of effect under investigation (Crocetti, 2016). To estimate the effect sizes of the studies, correlation coefficient from the square root of the given R squared value were created. The effects sizes were estimated as follows.

$$r = \sqrt{R^2} \tag{1}$$

Since R^2 is always positive, this transformation alone does not reveal whether the underlying relationship was positive or negative. To determine the correct sign of r, the direction of the relationship was cross-checked against the reported regression coefficients. A positive β yielded a positive r, while a negative β produced a negative r. This ensured that the resulting effect sizes faithfully reflected the directionality of the relationships under study. Once the correlation coefficient r was obtained, it was converted to Fisher's Z (Zr) in order to stabilise the variance and allow for meta-analytic pooling. Some meta-analysis use Fisher's z-transformed correlation for data analysis (Card, 2015). The transformation used was as follows:

$$z_\Gamma = \frac{1}{2}\ln\left(\frac{1+\Gamma}{1-r}\right) \tag{2}$$

The variance of Fisher's Z value was estimated using the sample size (n) reported in the primary study. It should be noted that random-effects meta-analysis of correlation coefficients causes biased meta estimates and, in order to account for that, Stanley and Doucouliagos (2023) said that Fisher's z-transformation should be used to remove most of the bias of the meta-analysis of the correlations. Fisher's transformation of correlations which has a known variance,$1/(n-3)$. Fisher's z Transformation is the conventional solution to the dependence of correlation's variance to its estimated value (Stanley et al., 2024).

$$v = \frac{1}{n-3} \tag{3}$$

This approach allowed all studies whether they originally reported regression models, R^2 values, or partial statistics to be expressed in a common effect-size metric. The Fisher's Z values, along with their variances, were then used as the inputs for the random-effects meta-analysis conducted in SPSS. After pooling, the Fisher's Z values were back-transformed into correlation coefficients (r) to facilitate interpretation. Effect sizes were computed using the

regression coefficient (β) and its standard error (SE) reported in each study. These were entered into SPSS, which calculated the corresponding weights and 95% confidence intervals for inclusion in the meta-analysis.

The statistical analysis took place in several stages. First, a pooled effect size was calculated using a random-effects model chosen because the studies varied widely in their contexts and methods as supported by (Grewal, 2018), who states that with random-effect models, studies are not assumed to come from the same population, and each study estimates a unique parameter. Thus, the researcher uses a random-effects model. Q and I^2 tests were used to test the homogeneity between effect sizes. Steel et al. (2015) used the Q statistics test the null hypothesis of homogeneity versus heterogeneity. The study estimates the effects of behavioural biases on effects size or investment decisions by a regression model that is specified as follows.

$$\begin{aligned} Effect\ size_{it} = {} & \beta_o + \beta_1 Overconfidence_{it(-1)} + \beta_2 Herding_{it} \\ & + \beta_3 Mental\ Accounting_{it} + \beta_4 Regret\ Aversion_{it} + \beta_5 Anchoring_{\ it} \\ & + \beta_6 Regret\ Aversion_{it} + \beta_7 Loss\ Aversion_{it} + \beta_8 Representative_{it} \\ & + \beta_9 Disposition\ Effect_{it} + \beta_{10} Hindsight_{it} + \varepsilon i \end{aligned}$$

Studies were included if they investigated one or more behavioural biases in relation to investment decisions, reported statistical findings that could be extracted. Duplicates studies, studies that lacked relevant data, or were unrelated to the core theme were excluded. These studies were search from different databases such as Web of Science, Google Scholar, Norwegian List, ScienceDirect, ISI, Scopus, SciELO, and bibliographies of related studies using a combination of Boolean operators and thematic keywords that include and are not limited to "behavioural biases" OR "overconfidence" OR "herding behaviour" OR "regret aversion" OR "hindsight" …. AND "Investment decision". The process of narrowing down the studies followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which provide a clear and transparent framework for documenting the flow of information.

4. RESULTS AND DISCUSSION

The main objectives and questions of the research were to establish the extent to which behavioural biases affect investors decision making. Firstly, the study provided the descriptive statistics of the study, then correlational analysis of continuous data variables. The study further meta regression and egger regression.

4.1 Descriptive Statistics

Descriptive statistics are a set of statistical methods that summarise, organise, and present data in a clear and meaningful way. By incorporating metrics such as mean, minimum and maximum values, standard deviation, and standard error in this section, the study demonstrated general patterns, trends, and variations. The large dispersion indicated by the standard deviation shows considerable heterogeneity among the included studies. The average slope of the bias of 0.085 indicates a positive association between behavioural biases and investment decisions in most studies. The results are depicted in Table 1.

Table 1. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Error	Std. Deviation
Sample size	64	13	2168	258.48	34.922	279.373
Slope of the biases	64	-4.270	0.645	0.085	.075285	.602280
Test statistic	64	-9.227	13.159	2.75144	.513742	4.109939
R Squared	64	.033	.934	.43217	.028902	.231216
Probability Value	64	.000	.946	.18328	.033582	.268654
Standard Error	64	.01	2.80	.3184	.07075	.56602
Effect size	64	-.79	0.97	.4242	.06327	.50618
Valid N (listwise)	64					

Source: Author's work (2025)

The effect size mean signifies a medium-to-large behavioural effect. This shows that behavioural biases collectively have a practically meaningful impact on investment behaviour, reinforcing behavioural finance assertions that psychological factors significantly alter market decisions. These statistics depict a diverse body of empirical work, varying in scale and precision, yet consistently demonstrating that behavioural biases are non-trivial predictors of investor decision-making patterns.

4.2 Correlations

Pearson's correlation is a measure of an association between variables (Schober, 2018). The correlation analysis examines the strength and direction of the relationships between the control variables in the study.

Table 2. Pearson Correlations

	Effect Size	
	Correlation	**Sig. (2-tailed)**
Slope of the bias	0.475	<.001
Test Statistic	0.528	<.001
Probability value	-0.205	0.104
R Squared	0.38	0.002
Sample size	0.178	0.159
Standard Error	-0.136	0.285

Source: Author's work (2025)

Table 2 shows the Pearson correlation coefficients describing the direction and strength of relationship the effect size and the control variables used in the meta-analysis. The statistically robust finding in the correlational matrix is that there is a highly significant positive relationship between the Slope of the bias and the Effect Size. The Slope of the bias represents distortion caused by a cognitive error. A steeper slope implies a more pronounced deviation from rational behaviour.

4.3 Meta Analysis Regression

According to Baker (2009), meta-regression has been described as the merging of meta-analytic techniques with linear regression principles. Meta regression has grown in popularity in recent years; it is an integral part of a systematic review and utilises statistical techniques to pool data.

Table 3. Meta Regression Results

Parameter	Estimate	Standard Error	Test Statistic	Sig. 2 Tailed	Interval Confidence	
					Lower	Upper
(Intercept)	1.454	2.0550	.708	.483	-2.678	5.586
Overconfidence	.112	.1514	.741	.462	-.192	.416
Herding bias	-.059	.1455	-.404	.688	-.351	.234
Hindsight bias	.777	.1765	4.405	.001	.423	1.132
Representative bias	-.282	.1525	-1.846	.071	-.588	.025
Disposition Effect	-.274	.1211	-2.263	.028	-.517	-.031
Availability bias	-.101	.1572	-.644	.523	-.417	.215
Anchoring bias	-.184	.1270	-1.448	.154	-.439	.071
Loss Aversion	-.336	.2303	-1.459	.151	-.799	.127
Mental Accounting	-.378	.1679	-2.254	.029	-.716	-.041
Risk Aversion	-.458	1.8331	-.250	.804	-4.143	3.228
Slope of bias	.270	.3335	.810	.422	-.401	.941

Source: Authors work (2025)

Across studies, hindsight bias has a significant positive effect on investment decisions. It implies that studies accounting for hindsight bias tend to report significantly larger effect sizes, highlighting the importance of the bias in investor decision-making outcomes. It implies that investors who increases perceived predictability of past events, leading to stronger behavioural responses. However, the disposition effect and mental accounting bias have shown a significant negative effect on investment decision. It implies that the presence of mental accounting and the disposition effect dampen investment decisions. Regarding the disposition effect, the investors delays selling losing assets and make limited portfolio adjustment. With regards to mental accounting, investors do not quicky react to market signals. Representative bias has also shown a significant negative effect on investment decisions. When investors depict investment representative bias, they rely on this similarity instead of analysing risk, earnings and market trends. Therefore, reliance on pattern matching and not fully evaluations negatively affect investment decisions. Overconfidence, herding, availability, anchoring, loss aversion, and risk aversion are statistically insignificant, implying limited explanatory power to influence investment decisions.

4.4 Effect Size Estimates

Effect size refers to a statistical measure that quantifies the strength of a relationship. Unlike p-values, which only indicate the presence of an effect, effect sizes show how strong that effect is, making them crucial for interpreting the practical importance of research findings. The results of the effects sizes are depicted in Table 4

Table 4. Effect Size

	Effect Size	Std. Error	Z	Sig. (2-tailed)	Confidence Interval	
					Lower	Upper
Overall	.440	.0676	6.517	< .001	.308	.573

Source: Author's work (2025)

The overall analysis revealed a clear and meaningful positive link between behavioural biases and investment decision-making. The effect is statistically reliable, indicating that the impact of behavioural biases on investor choices is consistent across studies.

4.5 Publication Bias Tests

This section evaluates whether the collected studies suffer from publication bias, this is the tendency for studies with significant or favourable results to be published more often than those with non-significant outcomes (Rothstein, Sutton, and Borenstein, 2005). The Egger's Regression test, Homogeneity test, Heterogeneity test has been conducted. The results of the Egger's Regression test are depicted in Table 5.

Table 5. Egger Regression Test

Parameter	Coefficient	Standard Error	T-value	Sig. (2 tailed)	Confidence Interval	
					Lower	Upper
(Intercept)	9.630	38.0779	.253	.801	-67.016	86.277
Standard Error	.286	.4042	.709	.482	-.527	1.100
Overconfidence	.063	.2539	.246	.806	-.449	.574
Anchoring bias	-.169	.2517	-.670	.506	-.675	.338
Herding bias	-.063	.2509	-.253	.801	-.568	.442
Representative	-.234	.2547	-.919	.363	-.747	.279
Disposition effect	.025	.2437	.103	.919	-.466	.516
Availability bias	-.103	.2485	-.413	.682	-.603	.397
Mental Accounting	-.124	.2941	-.421	.676	-.716	.468
Risk aversion	-.113	.5181	-.219	.828	-1.156	.929
Regret aversion	.066	.2603	.253	.801	-.458	.590
hindsight bias	.684	.3069	2.230	.031	.067	1.302
Sample size of study	-7.034E-5	.0004	-.195	.846	-.001	.001
Slope of the bias	.154	.1511	1.016	.315	-.151	.458

Source: Authors work (2025)

The intercept is insignificant, indicating the absence of publication bias in the empirical studies included in the meta-analysis. The Egger regression has also demonstrated that hindsight bias has significant positive effect on effect sizes, indicating the presence of a systematic moderator effect. Biases such as overconfidence, anchoring, herding, representative, disposition effect, availability, mental accounting, risk aversion, and regret aversion are statistically insignificant, indicating the absence of a systematic moderator effect in all studies.

4.6 Test for Residual Homogeneity

Ziegler and Fiedler (2025) defined homogeneity as the inverse of standard deviation. It refers to the bandwidth to which the individual studies are consistent. Homogeneity tests the null

hypothesis that all effect sizes are equal across the included studies. The results of the Homogeneity tests are depicted in Table 6**.**

Table 6. Homogeneity

Chi-square (Q statistic)	Df	Sig.
1217.689	48	<.001

Source: Authors work (2025)

Residual Homogeneity tests the null hypothesis that multiplicative dispersion parameter is equal to 1. The null hypothesis for homogeneity was rejected. This suggests that substantial heterogeneity exists among the included studies. This situation occurs especially when the meta-analysis includes 10 or more studies and each of them has addressed the main research question differently from others (Crocetti, 2016).

4.7 Test for Heterogeneity

Heterogeneity is the degree to which a system diverges from a state of what is considered to be normal (Eliazar, 2018). Analysing the data in terms of heterogeneity provides a more accurate estimates of the effect sizes and offers some key knowledge into potential moderators.

Table 7. Heterogeneity

Tau-squared	.099
I-squared (%)	95.8
H-squared	23.906
R-squared (%)	57.4

Source: Authors work (2025)

The residual heterogeneity test was significant, confirming that substantial heterogeneity persisted after accounting for moderators. Based on the I-squared (%), 95.8% of the variance in effect sizes are explained by the differences between studies. The H-squared of 23.906, which is greater than 1 further indicates heterogeneity. R squared has further depicted that 57.4% of the variation in investment decisions is explained by the model. This implies that 47.6% of the changes are explained by other factors.

4.8 Model Coefficient Test

Model coefficients quantify the relationship between independent variables (predictors) and the dependent variable outcome (Wang, 2024). The results are depicted in Table 8.

Table 8. Coefficient test

Wald Chi-square[a]	Df	Sig.	
260.795	15	<.001	

Source: Author's work (2025)

The overall model coefficient test yielded a significant Wald Chi-square value indicating that the set of predictors included in the meta-regression jointly contributed to explaining the variability in effect sizes across studies. This suggests that behavioural bias categories and

study-level characteristics are meaningful moderators that influence the strength of the relationship between behavioural tendencies and investment decisions.

6. CONCLUSION

The study investigated the effects of behavioural biases on investment decisions using a systematic and meta-analysis protocol (PRISMA-P). After data search, 64 studies met the inclusion criterion. From the 64 studies, the study concluded that hindsight bias has a significant positive effect on investment decisions. It implies that studies accounting for hindsight bias tend to report significantly larger effect sizes, implying that investors who increase perceived predictability of past events make good investment decisions. However, the disposition effect and mental accounting bias have shown a significant negative effect on investment decision. Regarding the disposition effect, the investors delays selling losing assets and make limited portfolio adjustment. With regards to mental accounting, investors do not quicky reacts to market signals. Representative bias has further shown a significant negative effect on investment decisions. When investors depict investment representative bias, they rely on this similarity instead of analysing risk, earnings and market trends. The study further estimated the effects sizes; the study revealed a positive relationship between behavioural biases and investment decision making. The effect is statistically significant relationship indicates that the impact of behavioural biases on investor decisions is consistent across studies. The study further estimated the Egger regression and found that the intercept is insignificant, indicating the absence of publication bias in the empirical studies included in the meta-analysis. The Egger regression has also demonstrated that hindsight bias has significant positive effect on effect sizes, indicating the presence of a systematic moderator effect. Biases such as overconfidence, anchoring, herding, representative, disposition effect, availability, mental accounting, risk aversion, and regret aversion are statistically insignificant, indicating the absence of a systematic moderator effect in all studies.

Furthermore, residual Homogeneity tested the null hypothesis that multiplicative dispersion parameter is equal to 1. The null hypothesis for homogeneity was rejected, suggesting substantial heterogeneity among the included studies. The residual heterogeneity test was further conducted. Based on the I-squared (%), 95.8% of the variance in effect sizes are explained by the differences between studies. The H-squared of 23.906, which is greater than 1 further indicates heterogeneity. R squared has further depicted that 57.4% of the variation in investment decisions is explained by the model. Lastly, the model coefficient test yielded a significant Wald Chi-square value indicating that the set of predictors included in the meta-regression jointly contributed to explaining the variability in effect sizes across studies. The study recommends that financial literacy initiatives should include an element of behavioural finance teaching in order to promote more self-recognition and judgment. For financial advisors and portfolio managers, the results highlight the value of using behavioural insights in their advice. Advisers can create tools and strategies that help mitigate their clients' behavioural biases, such as implementing automatic stop-loss limits to counter the disposition effect or applying diversification rules to negate mental accounting. Policymakers and regulators can utilise these findings to build investor protection frameworks that account for human behaviour.

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