

Systematic Review

A PRISMA-Based Systematic Review of Behavioral Biases and Demographic Moderators in Investment Decision-Making

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Abstract

Behavioral finance challenges classical rational-investor models by demonstrating that psychological biases shape financial decisions. Evidence indicates that overconfidence, herding, loss aversion, and the disposition effect are not uniformly distributed but are shaped by gender, age, financial literacy, income, and investment experience. However, the literature remains fragmented across contexts and geographies. This PRISMA 2020 systematic review synthesizes 57 empirical studies (2010–2025) screened from 172 Scopus records and appraised against eight quality criteria. Findings confirm overconfidence (31 studies) and herding (26) as the most prevalent biases, concentrated among younger, male, and less experienced investors, whereas loss and risk aversion are more common among female, older, and financially insecure investors. Financial literacy emerges as the strongest moderator, reducing most biases while paradoxically amplifying overconfidence at moderate levels, consistent with the Dunning–Kruger effect. Formal moderation analyses (14 studies) support literacy as a significant boundary condition, and investment experience exhibits a non-linear pattern favoring moderate levels. This review contributes a structured, quality-appraised synthesis and a research agenda addressing intersectionality, longitudinal designs, and geographic diversity.

Keywords: behavioral finance; investment decision-making; demographic moderators; overconfidence; herding; financial literacy; systematic literature review; PRISMA

1. Introduction

Rational choice theory has long served as the cornerstone of traditional finance, holding that investors make decisions by systematically weighing risk and return. Expected Utility Theory (EUT), one of the foundational models, posits that investors maximize the expected utility of wealth under uncertainty, expressed as $EU = \sum_{i=1}^n p_i \cdot u(x_i)$, where p_i represents the probability of outcome i and its utility $u(x_i)$. The Efficient Market Hypothesis (EMH; Fama, 1970) builds upon this logic, asserting that asset prices reflect all available information at any given time.

However, decades of empirical investigation have fundamentally challenged these assumptions. Investors do not always make rational decisions due to cognitive limitations, emotional responses, and social influences. These systematic departures gave rise to behavioral finance, an interdisciplinary field that explains decision-making errors under uncertainty through insights from psychology, economics, and neuroscience (Kahneman & Tversky, 1979; Thaler, 1980; Simon, 1955). A central theoretical contribution of behavioral



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finance is prospect theory (Kahneman & Tversky, 1979), which models decisions relative to reference points, incorporates loss aversion ($\lambda > 1$), and captures diminishing sensitivity to outcomes through the value function $u(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda(-x)^\beta & \text{if } x < 0 \end{cases}$, where $\alpha, \beta \in (0, 1)$.

Behavioral biases, including overconfidence, herding, availability heuristics, anchoring, representativeness, loss aversion, regret aversion, and the disposition effect, have been documented across nearly every financial setting. Odean (1998) showed that overconfident investors trade more than is optimal, because they believe that they have better information. This has been found to be especially strong for men and produces lower net returns, as demonstrated by Barber and Odean (2001). Shiller (2000) associated herding behavior and irrational exuberance with asset bubbles.

One of the newer studies in the literature provides the critical insight that biases are not uniform. Demographic factors such as age, gender, financial literacy, income, and investment experience act as moderating variables in the size and type of biases. Lusardi and Mitchell (2014) provide evidence that financial literacy helps to mitigate cognitive biases. Older investors are more likely to be status quo-oriented and to preserve their capital, whereas young investors are more likely to be impulsive and to follow herding behavior, which can be amplified by social media (Grable & Joo, 2004). The evidence is strong that men have higher confidence in their investment skills than women and trade more and diversify less, as suggested by Barber and Odean (2001) and Biais et al. (2005).

These demographic moderators not only have academic relevance but also have practical applications for portfolio management, financial literacy programs, regulatory frameworks, and investment counseling. This is because demographic-based interventions are more effective than universal interventions since the cognitive structure of financial decision-making is systematically different between genders, ages, experiences, and socioeconomic statuses.

Although there has been a tremendous amount of research conducted in the field of behavioral finance, the literature is still divided. Very few studies consider multiple demographic factors or a broad range of biases together, thus limiting understanding. There are few cross-cultural and cross-country comparisons and there is variation in measurements and methodology that hinders synthesis. To our knowledge, no previous systematic review has included a quality-appraised sample of all the 57 studies with formal evidence of moderation and a full bias taxonomy across all major demographic dimensions.

To address these gaps, the present study performs a systematic literature review of empirical studies related to behavioral finance and demographic research in the context of investment decision-making by using the PRISMA 2020 methodology. In particular, this review aims to (1) identify and categorize the most common behavioral biases that impact investors in different contexts; (2) synthesize the effects of demographic characteristics, gender, age, financial literacy, investment experience and income on these biases; (3) review the formal moderation evidence from 14 studies; (4) systematically assess the quality of the studies; and (5) identify thematic patterns and contradictions that can guide future empirical research, financial advisory practices, and policy interventions.

2. Materials and Methods

This systematic review is conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework (Page et al., 2021), providing transparency, repeatability and rigor in the search, screening, quality assessment and synthesis of empirical research into the role of behavioral finance and demographic factors in the context of investment decision-making. The PRISMA checklist used is provided as Supplementary Materials.

2.1. Research Question

The guiding research question of this review is “How do demographic characteristics, including gender, age, financial literacy, income, and investment experience, moderate the expression of behavioral biases in investment decision-making, and what patterns and contradictions emerge across empirical contexts?”

Three subsidiary questions structure the analysis: (a) What behavioral biases are most prevalent across empirical studies, and with what frequency? (b) Which demographic variables function as moderators, determinants, or contextual factors in the bias-decision relationship? (c) What is the quality of the evidence base, and where do contradictions emerge?

2.2. Eligibility Criteria

Inclusion criteria were established prior to the search and applied at all screening stages. Studies were included if they (1) were empirical (quantitative, experimental, or mixed methods) and reported primary data; (2) examined at least one behavioral bias or behavioral construct in the context of investment or financial decision-making; (3) incorporated at least one demographic or sociodemographic variable (gender, age, education, income, financial literacy, or investment experience); (4) were published in peer-reviewed academic journals; and (5) were written in English. Excluded were conceptual papers, literature reviews, book chapters, conference papers, studies with no quantifiable behavioral construct, and studies without English full-text access.

2.3. Data Sources and Search Strategy

The literature search was conducted in the Scopus database. The Boolean search string was structured as follows:

TITLE-ABS-KEY (“behavioral finance” OR “investment biases” OR “investor psychology”) **AND TITLE-ABS-KEY** (“investment decision” OR “financial decision-making” OR “risk perception”) **AND TITLE-ABS-KEY** (“demographics” OR “age” OR “gender” OR “financial literacy” OR “income level” OR “education”).

The search covered publications from 2010 to 2025 to capture the development of behavioral finance as an empirical field while maintaining focus on contemporary findings. The final search yielded 172 records.

2.4. Screening and Selection Process

Screening followed the PRISMA 2020 four-stage process. Stage 1 (Identification): 172 records were identified from Scopus. After applying article-type filter (journal articles only), 136 records remained. After restricting to English-language publications, 133 records remained. Stage 2 (Title-Abstract-Key-word screening): 125 records remained after removing 8 for being irrelevant. Stage 3 (Retrieval): 49 records could not be retrieved for full-text review due to institutional access limitations after accounting for all available access channels; 76 records proceeded to full-text eligibility assessment. Stage 4 (Eligibility assessment): Full-text review applying the inclusion/exclusion criteria and quality appraisal resulted in the exclusion of 19 additional records, yielding a final sample of 57 studies. The PRISMA 2020 flow diagram is presented in Figure 1.

2.5. Quality Appraisal

This review includes a formal quality appraisal of all 57 included studies. Each study was assessed against eight criteria adapted from the Mixed Methods Appraisal Tool (MMAT) and the Newcastle–Ottawa Scale for observational studies:

Each criterion was rated as Clearly Met (CM), Partially Met (PM), or Not Reported (NR). Studies were assigned an overall quality rating of High (CM on 7–8 criteria),

Moderate–High (CM on 5–6), Moderate (CM on 4, PM on others), or Moderate–Low (CM on fewer than 4). Table 1 presents the quality appraisal results for all 57 studies.

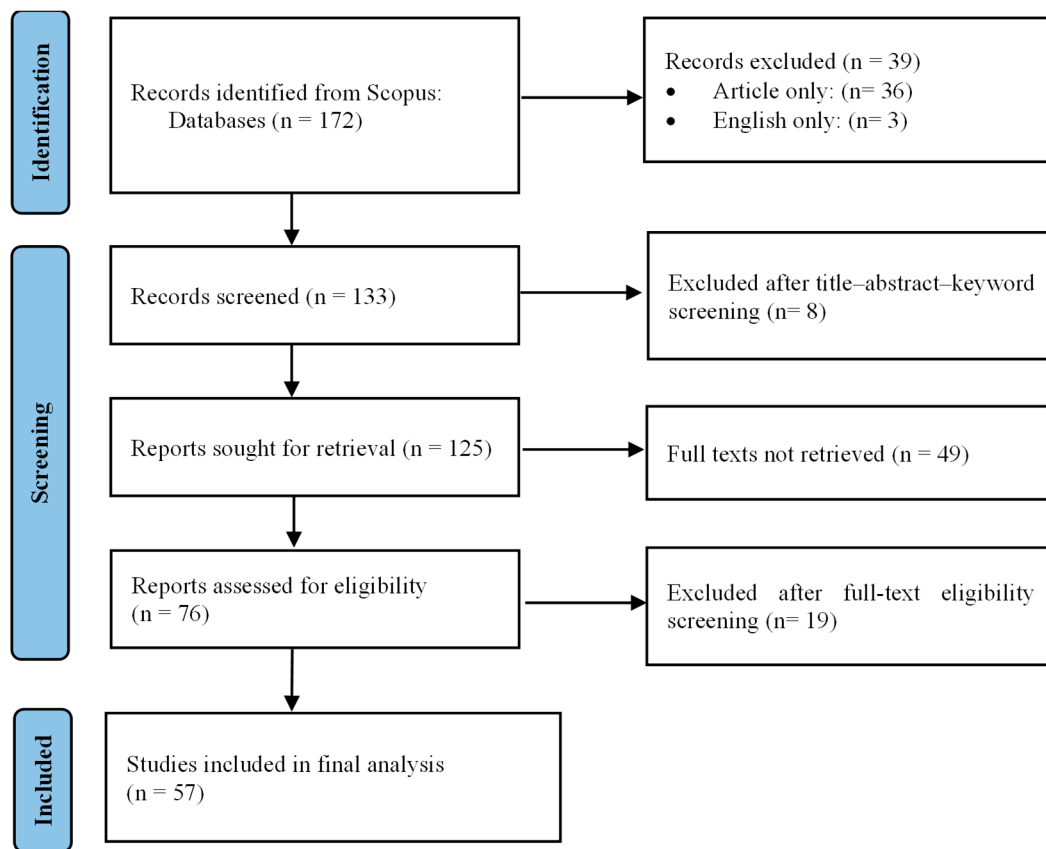


Figure 1. Prisma 2020 flow diagram for influence of demographics on behavioral finance review.

Table 1. Quality appraisal of all 57 included studies.

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Overall
(Nga & Ken Yien, 2013)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Döbeli & Vanini, 2010)	CM	CM	PM	PM	CM	CM	CM	PM	Mod–High
(Walia & Kiran, 2012)	CM	CM	PM	NR	CM	CM	PM	PM	Moderate
(Lim et al., 2020)	CM	CM	PM	CM	CM	CM	CM	PM	Moderate
(Bateman et al., 2011)	CM	CM	CM	CM	CM	CM	CM	CM	High
(A. Chandra et al., 2017)	CM	CM	PM	NR	CM	CM	PM	PM	Moderate
(Jamaludin & Gerrans, 2015)	CM	CM	CM	CM	CM	CM	CM	CM	High
(McCannon & Peterson, 2015)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Raut, 2020)	CM	CM	PM	CM	CM	CM	CM	PM	Mod–High
(Bartholomae et al., 2019)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Linge et al., 2024)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Papadovasilaki et al., 2018)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Kleffel & Muck, 2024)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Prakash & Alagarsamy, 2022)	CM	CM	PM	PM	CM	CM	PM	PM	Moderate
(Budsaratagoon et al., 2015)	CM	CM	PM	NR	CM	CM	PM	PM	Moderate
(Israel et al., 2019)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Tomar et al., 2021)	CM	CM	CM	CM	CM	CM	CM	PM	Mod–High
(Strydom et al., 2018)	CM	CM	CM	CM	CM	CM	CM	PM	Mod–High
(Khawaja & Alharbi, 2021)	CM	CM	PM	PM	CM	CM	PM	PM	Moderate
(Renerte et al., 2023)	CM	CM	CM	CM	CM	CM	CM	CM	High

Table 1. Cont.

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Overall
(Djuachiriaty et al., 2024)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Oehler et al., 2018)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Ahmad & Shah, 2022)	CM	CM	PM	CM	CM	CM	CM	PM	Mod-High
(Kumar et al., 2023)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(R et al., 2025)	CM	CM	PM	PM	CM	CM	PM	PM	Moderate
(Ladrón de Guevara Cortés et al., 2023)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Uma & Maheswari, 2025)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Srivastava et al., 2025)	CM	PM	PM	NR	CM	CM	PM	PM	Mod-Low
(Nga, 2020)	CM	CM	PM	CM	CM	CM	CM	PM	Mod-High
(Rad et al., 2025)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Metawa et al., 2019)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Wahba et al., 2025)	CM	CM	PM	PM	CM	CM	PM	PM	Moderate
(Sachdeva & Lehal, 2024)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(R. Chandra et al., 2025)	CM	CM	PM	CM	CM	CM	CM	PM	Mod-High
(Okumura et al., 2023)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Almansour et al., 2025)	CM	CM	PM	PM	CM	CM	PM	PM	Moderate
(Weiss-Cohen et al., 2022)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Schall, 2020)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Darwish, 2025)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Safford et al., 2018)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Agarwal et al., 2025)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Hamurcu et al., 2025)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Putri Pa et al., 2022)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Murhadi et al., 2024)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Raghu et al., 2025)	CM	CM	PM	NR	CM	CM	PM	PM	Moderate
(Rasool & Ullah, 2020)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(van Dolder & Vandenbroucke, 2024)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Hafenstein & Bassen, 2016)	CM	CM	CM	CM	CM	CM	CM	CM	High
(Khatik et al., 2021)	CM	CM	PM	NR	CM	CM	CM	PM	Moderate
(Gopal et al., 2025)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Khilar & Singh, 2019)	CM	PM	PM	NR	PM	PM	PM	PM	Mod-Low
(Sabir et al., 2019)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Syukur et al., 2025)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Hafez, 2021)	CM	CM	PM	PM	CM	CM	CM	PM	Moderate
(Wang & Zou, 2024)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Kulkarni et al., 2025)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High
(Mahmood et al., 2024)	CM	CM	CM	CM	CM	CM	CM	PM	Mod-High

CM = Clearly Met; PM = Partially Met; NR = Not Reported. Q1: objectives; Q2: design; Q3: sampling; Q4: data collection; Q5: analysis; Q6: findings; Q7: limitations; Q8: reporting risk.

2.6. Data Extraction and Thematic Synthesis

Data extraction followed a pre-specified structured form capturing study ID (author, year), country, market classification, sample size and type, data collection method, analytical technique(s), behavioral biases examined (with measurement approach), demographic variables included, type of demographic analysis (descriptive, predictor, formal moderation), and key statistical findings.

3. Results

The final sample comprised 57 empirical study records spanning 19 countries and 7 global regions. Geographically, the literature was concentrated in South Asia ($n = 21$, 36.8%), driven primarily by studies from India and Pakistan. When combined with South-east Asia ($n = 10$, 17.5%), South and Southeast Asia accounted for 31 studies (54.4%) of the sample. Europe contributed 11 studies (19.3%), followed by the Middle East and

North Africa ($n = 7$, 12.3%), North America ($n = 4$, 7.0%), and Oceania and South America ($n = 2$ each, 3.5%). At the country level, India was the most frequently represented setting ($n = 17$, 29.8%), followed by Germany and Indonesia ($n = 5$ each, 8.8%). Malaysia, Pakistan, and the United States each contributed four studies (7.0%), while Egypt contributed three studies (5.3%). Australia, Saudi Arabia, and the United Kingdom each contributed two studies, and the remaining countries were represented by one study each, reflecting a broad but uneven global distribution.

Temporal analysis indicated a marked acceleration in research output over time. Publication years ranged from 2010 to 2025, with all study records reporting a clear publication year. Output remained modest from 2010 to 2018 ($n = 13$, 22.8%), then increased substantially from 2019 onward ($n = 44$, 77.2%). The years 2024 ($n = 8$) and 2025 ($n = 14$) alone accounted for 22 studies (38.6%) of the total sample, reflecting the rapid recent growth of this field. A two-panel figure was generated summarizing (a) country-level contributions and (b) temporal trends (Figure 2).

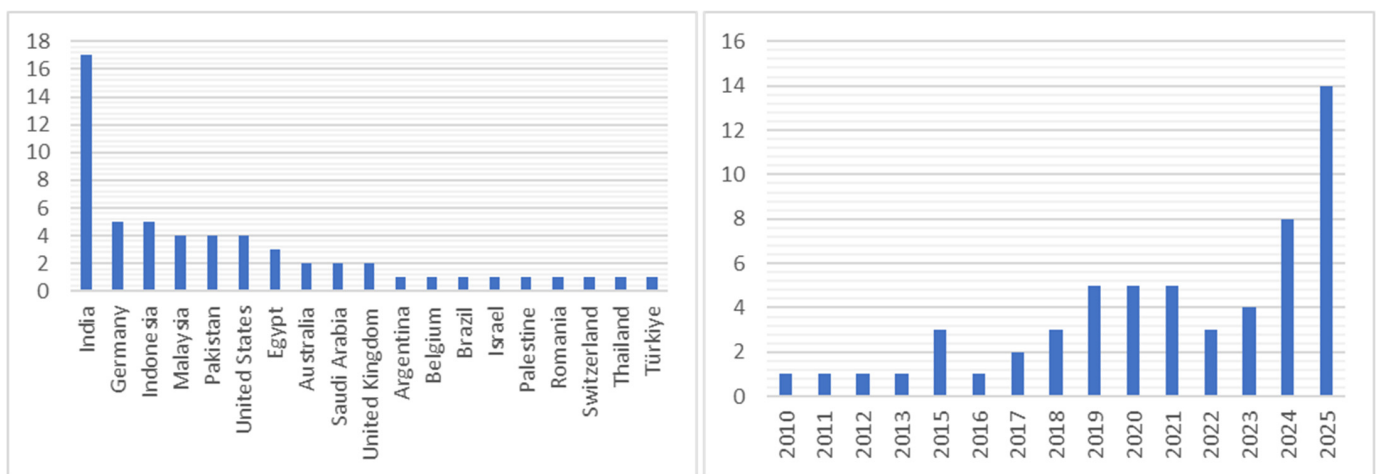


Figure 2. Publication count summary.

Sample sizes ranged from 68 participants (Döbeli & Vanini, 2010) to 3740 participants (van Dolder & Vandenbroucke, 2024), with a median of approximately 360–365 participants. The most common study designs were cross-sectional surveys ($n = 38$), laboratory experiments ($n = 10$), and mixed designs or field experiments ($n = 9$). For full transparency, Appendix A Table A1 provides complete bibliographic, methodological, and demographic details for all 57 included studies.

3.1. Quality of Included Studies

Quality appraisal results are presented in Table 1. Of the 57 studies, 14 (24.6%) were rated High quality, 18 (31.6%) Moderate–High, 23 (40.4%) Moderate, and 2 (3.5%) Moderate–Low. Laboratory experiments and large-scale field studies consistently achieved higher quality ratings, as they more often reported sampling procedures, inter-rater reliability, and validity measures. Cross-sectional surveys from emerging markets frequently received Moderate ratings due to incomplete reporting of sampling methods, response rates, and ethical approval procedures.

The most common quality concern across studies was incomplete reporting of sampling method (Q3, Partially Met in 30 studies) and data collection rigor, including response rates and inter-rater agreement (Q4, Partially Met in 18 studies, Not Reported in 7 studies). Risk of selective reporting (Q8) was Partially Met in 43 studies, reflecting the absence of pre-registration and limited conflict-of-interest disclosure in the behavioral finance empirical literature generally.

These quality findings are reported transparently and are used to weigh the discussion: where findings rest predominantly on Moderate-quality studies, we flag this and distinguish them from conclusions supported by High or Moderate–High-quality evidence.

To complement the quality appraisal and provide a macro-level view of the conceptual architecture of this literature, a keyword co-occurrence network was generated from author-assigned keywords of all 57 included studies (Figure 3). The network reveals seven distinct thematic clusters that align closely with the overarching themes identified in this review, while also exposing structural features of the field that have implications for future research.

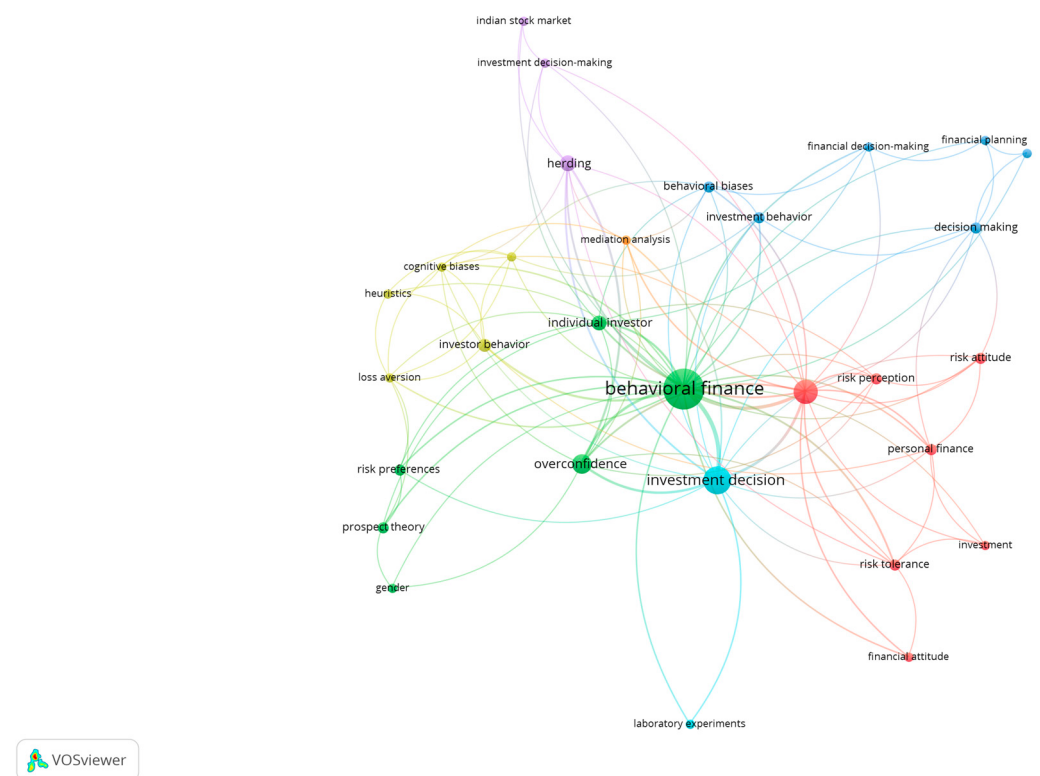


Figure 3. Keyword co-occurrence network of 57 included studies (author keywords; minimum co-occurrence = 2; N = 30 nodes).

Behavioral finance is in the gravitational center. The largest node in the network is “behavioral finance”, which is connected with the nodes “gender”, “individual investor”, “overconfidence”, “prospect theory” and “risk preferences” in Cluster 2 (green). This centrality is also indicative of the organizing function of the field, yet the co-location of individual-difference variables suggests that behavioral finance is structurally embedded in demographic and psychological heterogeneity and does not exist as a separate meta-construct. The node acts as the main link between all other clusters, linking risk perception constructs (Cluster 1), applied decision research (Cluster 3), cognitive–heuristic processes (Cluster 4), market-level herding (Cluster 5), experimental methods (Cluster 6) and analytical techniques (Cluster 7).

The evaluative cluster is made up of risk and financial attitude. The key evaluative and perceptual constructs from the literature are grouped together in Cluster 1 (red: financial attitude, financial literacy, investment, personal finance, risk attitude, risk perception, risk tolerance). The concentration of risk-related terms alongside financial literacy and personal finance reflects the continued emphasis of the field on how investors assess uncertainty. Financial literacy in this configuration is not a cross-cutting moderator across all cognitive domains but rather operates within a risk calibration nexus. It appears to be related to both theoretical and applied dimensions through its connections with behavioral finance and

investment decision, while its embedding in the structure of risk perception suggests that literacy effects are likely to be mediated by subjective risk judgments.

Decision research for emerging markets combines behavioral and contextual constructs. The applied survey-based stream of research, focused on emerging markets, falls under Cluster 3 (blue: behavioral biases, decision-making, financial decision-making, financial planning, investment behavior, Malaysia). The term “behavioral biases” was included in this cluster and not in the theoretically oriented cognitive cluster, indicating that in the current literature, the term is used more as an applied description of observed deviations, rather than as a well-theorized construct. The geographic concentration of empirical work in the emerging Southeast Asian economies is reflected in the presence of Malaysia. The cluster shows a methodological separation between survey-based applied research and theoretically driven experimental work, which is emphasized by the separation of “investment decision” (Cluster 6) from “cognitive biases” (Cluster 4).

The core of the cognitive–behavioral approach is a unique psychological cluster known as the cognitive–behavioral core. Theoretically grounded cognitive constructs are combined with investor behavior research in Cluster 4 (yellow green: cognitive biases, heuristics, investor behavior, loss aversion, psychological factors). The distinction of “cognitive biases” and “heuristics” from the more general “behavioral biases” term in Cluster 3 suggests a terminological and methodological split: Cluster 3 encompasses the more general topic of applied survey research while Cluster 4 contains the literature on mental shortcuts and loss-driven behavior. Loss aversion’s appearance here ensures its theoretical connection to prospect theory in Cluster 2, through risk preferences, but also keeps it separate from the applied bias literature.

Overconfidence and gender are tightly linked in the cluster of individual differences, as is the case for prospect theory. In Cluster 2 (green: behavioral finance, gender, individual investor, overconfidence, prospect theory, risk preferences), the demographic and theoretical constructs are at the center of the network. A closer theoretical fit between overconfidence, prospect theory and gender is apparent when these individual differences are co-located within the same cluster, more than is visible in the broader applied clusters. Only a small number of studies formally tested gender as a moderator, as it is structurally an “input” variable linked to the core and rarely used as an interactive boundary condition across the clusters.

Herding is methodologically isolated in a market-specific group. Cluster 5 (purple: herding, Indian stock market, investment decision-making) maintains its tight coupling with emerging-market contexts. The separation between herding (Cluster 5) and overconfidence (Cluster 2) provides a visual representation of a key finding in the synthesis: the study of herding is mostly at the market-level or social level in emerging markets while overconfidence is grouped with individual-level demographic and theoretical constructs. This is because there is a limited direct link between these clusters, as there is very little research that has directly tested the interaction between herding and overconfidence.

There are still methodological and terminological differences. The constructs in Cluster 6 (teal: investment decision, laboratory experiments) differ from those in Cluster 3 (financial decision-making constructs) and map to the methodological distinction between experimental designs and survey-based, cross-sectional studies. The co-occurrence of investment decision and laboratory experiments confirms that this combination is the most dominant in theoretically driven experimental research, while financial decision-making is the most important in applied survey research in emerging markets. There was a lack of conceptual linkage between these terms, signifying limited conceptual integration across methodological traditions.

Mediation analysis is a unique methodological bridge. Cluster 7 (orange: mediation analysis) forms a one-node cluster around the center of the network, and is connected to the cognitive-behavioral (Cluster 4), applied decision (Cluster 3), and individual difference clusters (Cluster 2). The structural isolation of this is analytically meaningful: mediation analysis has been growing in popularity within the behavioral finance research community, especially in SEM-based papers, but is not yet as connected with other methodological keywords as it could be. Its links to other clusters suggest that it is a technical bridge, but its absence from the other methodological terms suggests that analytical techniques are still not fully represented as keywords in the literature.

Implications for the field. The network is consolidated in seven clusters indicating some thematic refinement in the research on behavioral finance moderators, but there is still a lot of structural fragmentation. The central bridging role of behavioral finance is one of its strengths, but the separation of herding from overconfidence, embedding financial literacy in risk perception instead of as a universal moderator and peripheral isolation of mediation analysis suggest that theory-driven integration is still incomplete. The tighter coupling of overconfidence with prospect theory and gender (Cluster 2) and the separation of cognitive biases (Cluster 4) from applied behavioral biases (Cluster 3) suggest that researchers should attend more carefully to terminological precision and to methodological integration across experimental and survey paradigms. The limited inter-cluster density between experimental and survey traditions supports the call for pre-registered interaction-term models that would strengthen the theoretical core of the network.

3.2. Behavioral Biases Identified

Across the 57 reviewed studies, 17 distinct behavioral biases and behavioral constructs were identified. Table 2 summarizes bias frequencies and primary demographic associations.

Table 2. Behavioral biases, frequency and demographic associations.

Behavioral Bias/Construct	Frequency (Studies)	Primary Demographic Associations
Overconfidence	31	Young investors; male investors; novice investors; moderate financial literacy
Herding behavior	26	Young investors; female investors (some contexts); low financial literacy; low experience
Loss aversion	18	Older investors; female investors; financially insecure investors; highly educated
Risk aversion	17	Female investors; older investors; married investors; financially insecure
Disposition effect	13	Female investors; married investors; older investors; moderate-high experience
Anchoring	11	Less financially literate; less experienced investors
Availability bias	10	Less financially literate; less experienced; younger investors
Confirmation bias	8	Older investors; highly educated; experienced investors
Regret aversion	7	Married investors; older investors; loss-averse profiles
Framing effects	7	Context-dependent; influenced by communication style and product description

Table 2. *Cont.*

Behavioral Bias/Construct	Frequency (Studies)	Primary Demographic Associations
Status quo bias	5	Older generations (Boomers, Gen X); highly educated; experienced investors
Representativeness	5	Less financially literate; male investors with moderate experience
Social/community influence (herding-adjacent)	4	Gen Z investors; socially connected; platform-driven investors
Gambler's fallacy	4	Less financially literate; moderate experience investors
Affect heuristic/sustainability bias	3	Higher income; higher education; values-driven investors
Pro-environmental/psychic return	2	High-income; highly educated; older male investors
Hyperbolic discounting/decision inconsistency	2	Investors with inconsistent or low financial literacy

Overconfidence was the most prevalent bias, appearing in 31 studies (53% of the sample). It was most consistently associated with younger investors, male investors, and those with moderate rather than low or high financial literacy, consistent with the Dunning–Kruger effect. Herding behavior appeared in 26 studies (45%) and was particularly prevalent among novice investors, younger cohorts, and in emerging-market contexts where information asymmetry and social influence are heightened.

Loss aversion (18 studies) and risk aversion (17 studies) exhibited a distinct demographic profile, predominantly older investors, female investors, and those in financially insecure positions, consistent with prospect theory predictions regarding reference-point sensitivity and the steeper slope of the value function in the loss domain. The disposition effect (13 studies) overlapped substantially with loss aversion and was more prevalent in experienced investor samples.

Anchoring (11 studies) and availability bias (10 studies) were common across demographic groups but particularly pronounced in low-literacy samples. Confirmation bias (8 studies) showed an intriguing demographic pattern: rather than declining with education, it was more frequently observed in older and highly educated investors, consistent with motivated reasoning theory (Nickerson, 1998). This finding runs counter to the assumption that education protects against all biases.

Framing effects (seven studies) were largely context-dependent and strongly influenced by how financial products and decisions were presented, with simplified communication reducing gender gaps in financial product uptake (Döbeli & Vanini, 2010). Social influence or community-driven behavior (four studies) was predominantly observed among Gen Z investors interacting with digital platforms and online investment communities.

3.3. Demographic Moderators of Behavioral Biases

A critical contribution of this review is the explicit distinction between studies that the explicit distinction between studies that (a) treat demographic variables as descriptive background characteristics; (b) test demographics as predictors of biases or investment outcomes; and (c) conduct formal moderation analyses using interaction terms, multi-group analysis (MGA), or equivalent approaches. Of the 57 studies, 27 (47%) treated demographics primarily descriptively, 16 (28%) modeled demographics as predictors, and 14 (25%) conducted formal moderation analyses. Tables 3–7 synthesize findings across all five demographic dimensions with contradictions flagged.

Table 3. Impact of gender on behavioral biases and investment decisions.

Gender Dimension	Studies (n)	Key Sources	Contradictions/Caveats
Male investors show higher overconfidence	31	Barber and Odean (2001); Ahmad and Shah (2022); Renerte et al. (2023); Wang and Zou (2024); Rasool and Ullah (2020)	Consistent across markets; effect size varies with financial literacy levels
Male investors take more risk and trade more aggressively	23	Papadovasilaki et al. (2018); Israel et al. (2019); Prakash and Alagarsamy (2022); Bateman et al. (2011)	Stronger in laboratory settings; somewhat attenuated in real investment data
Female investors display greater risk aversion	17	Jamaludin and Gerrans (2015); Linge et al. (2024); van Dolder and Vandenbroucke (2024); Hamurcu et al. (2025)	More pronounced in emerging markets; partially driven by differences in financial knowledge
Female investors show greater herding (some contexts)	11	Nga and Ken Yien (2013); Sachdeva and Lehal (2024); Djuachiriaty et al. (2024)	Context-dependent; herding among women may reflect risk-sharing rather than irrationality
Gender differences reduce with financial literacy	14	Döbeli and Vanini (2010); Kumar et al. (2023); Tomar et al. (2021); Sabir et al. (2019)	Simplified communication and financial education close gender gap significantly
Gender is non-significant after controls	9	Murhadi et al. (2024); Bartholomae et al. (2019); Sachdeva and Lehal (2024); Kulkarni et al. (2025)	Effect disappears when financial literacy, income, or education are controlled for

Table 4. Impact of age on behavioral biases and investment decisions.

Age Dimension	Studies (n)	Key Sources	Contradictions/Caveats
Younger investors (Gen Z/Millennials): overconfidence, impulsivity, herding	24	Syukur et al. (2025); Kumar et al. (2023); R. Chandra et al. (2025); Bateman et al. (2011)	Digital environment amplifies herding; overconfidence decreases with market experience
Older investors: greater loss aversion and risk aversion	19	van Dolder and Vandenbroucke (2024); Hafez (2021); Bateman et al. (2011); Hamurcu et al. (2025)	Age effect on loss aversion is robust; interacts with wealth and financial security
Older investors: status quo and confirmation bias	11	Wang and Zou (2024); Schall (2020); Hafenstein and Bassen (2016)	Experienced investors over-rely on established heuristics
Age improves financial literacy in some contexts	13	Kumar et al. (2023); Walia and Kiran (2012); Agarwal et al. (2025)	Reversed in some countries where younger cohorts have digital literacy advantage
Generational patterns: Gen X/Boomers vs. Gen Z/Y	7	Syukur et al. (2025)	Generational framing adds useful structure but publication-year clustering limits inference
Age is non-significant after controls	5	Murhadi et al. (2024); Bartholomae et al. (2019); Sachdeva and Lehal (2024)	Age effect mediated by financial literacy and investment experience in several models

Table 5. Impact of financial literacy on behavioral biases and investment decisions.

Financial Literacy Dimension	Studies (n)	Key Sources	Contradictions/Caveats
Low financial literacy → herding, availability bias, overreaction	21	Sabir et al. (2019) ; Rasool and Ullah (2020) ; Khatik et al. (2021) ; Agarwal et al. (2025)	Relationship is strongest in emerging market samples; effect partially mediated by digital access
Moderate financial literacy → overconfidence amplification	16	Wang and Zou (2024) ; Murhadi et al. (2024) ; Ahmad and Shah (2022) ; Kulkarni et al. (2025)	Familiarity without full expertise breeds overconfidence, consistent with Dunning–Kruger logic
High financial literacy reduces most biases	22	Hamurcu et al. (2025) ; Tomar et al. (2021) ; Agarwal et al. (2025) ; van Dolder and Vandenbroucke (2024)	High literacy still increases overconfidence in some studies; see Wang and Zou (2024)
Financial literacy moderates bias effects (formal moderation)	11	Ahmad and Shah (2022) ; Sabir et al. (2019) ; Kulkarni et al. (2025) ; Darwish (2025) ; Mahmood et al. (2024)	Moderating role of FL is inconsistent: significant in some, non-significant in others
Digital financial literacy: Gen Z-specific improvement	5	Khatik et al. (2021) ; R. Chandra et al. (2025) ; Rad et al. (2025) ; Kumar et al. (2023)	Platform-mediated literacy may improve decision quality but increase herding simultaneously
Inconsistent/partial financial literacy → decision inconsistency	4	Putri Pa et al. (2022) ; Hamurcu et al. (2025) ; Wahba et al. (2025)	Attitude–behavior mismatch when knowledge is partial but confidence is high

Table 6. Impact of investment experience on behavioral biases and investment decisions.

Experience Dimension	Studies (n)	Key Sources	Contradictions/Caveats
Low experience → overconfidence, herding, reliance on social cues	18	Almansour et al. (2025) ; Sabir et al. (2019) ; Djuachiriaty et al. (2024) ; Khilar and Singh (2019)	Effect is robust; novice investors' overconfidence often self-reinforced by early gains
Moderate experience (≈5–10 yrs) → best performance and balance	9	Hafez (2021) ; Bateman et al. (2011) ; Raut (2020)	Non-linear relationship: moderate experience captures learning without reinforced bad habits
High experience → disposition effect and status quo bias	13	Murhadi et al. (2024) ; Wang and Zou (2024)	Experience reinforces patterns; disposition effect is stronger in experienced traders
Experience moderates herding	7	Syukur et al. (2025) ; Sabir et al. (2019) ; Murhadi et al. (2024)	Gen X benefited most from experience buffering herding; Gen Z did not
Past performance increases confidence-driven herding	6	Sabir et al. (2019) ; Gopal et al. (2025) ; Agarwal et al. (2025)	Positive feedback loop: success → overconfidence → herding → amplified losses in downturns
Experience is non-significant when literacy dominates	4	Murhadi et al. (2024) ; Raut (2020) ; Kulkarni et al. (2025)	In high-literacy samples, experience adds marginal predictive value

Table 7. Impact of income on behavioral biases and investment decisions.

Income Dimension	Studies (n)	Key Sources	Contradictions/Caveats
Higher income → lower herding, lower overconfidence, better market knowledge	14	Walia and Kiran (2012); Murhadi et al. (2024); Schall (2020)	Effect partially mediated by financial literacy and access to professional advice
Lower income → greater herding and availability bias	11	Almansour et al. (2025); Khatik et al. (2021)	Lower income correlated with lower financial literacy, making independent effects hard to isolate
Middle income → loss aversion and disposition effect	8	Hamurcu et al. (2025); van Dolder and Vandenbroucke (2024); Linge et al. (2024)	Wealth preservation motive intensifies loss aversion in middle-income bracket
High income → values-driven investing (ESG/SRI)	4	Schall (2020); Hafenstein and Bassen (2016); Kleffel and Muck (2024)	High-income investors show sustainability preferences but also increased status quo bias
Income is non-significant after controls	7	Hafez (2021); Bartholomae et al. (2019); Sachdeva and Lehal (2024)	Income effect often absorbed by education and financial literacy variables in SEM models

3.3.1. Gender

Gender was the most widely examined demographic variable, featuring in 45 of the 57 studies. The dominant finding, supported by 23 High- and Moderate-High-quality studies, is that male investors display significantly higher levels of overconfidence and take more risk than female investors. This pattern is consistent with Barber and Odean's (2001) foundational finding and is robust across emerging markets (e.g., Ahmad & Shah, 2022; Rasool & Ullah, 2020) and developed markets (e.g., Israel et al., 2019; Papadovasilaki et al., 2018; Bateman et al., 2011).

Female investors display greater risk aversion and loss aversion (17 studies) and in some contexts greater herding (11 studies). However, the herding pattern among women is context-dependent and may reflect adaptive risk-sharing rather than irrational information-following. Ladrón de Guevara Cortés et al. (2023) found that females were more conservative in gain domains but more aggressive in certain loss-domain choices, a prospect theory-consistent finding that complicates the simple narrative of female risk aversion.

Critically, nine studies found gender effects non-significant after controlling for financial literacy, income, or experience. Döbeli and Vanini (2010) demonstrated that simply presenting financial products in plain language eliminated the gender gap in structured-product ownership. This suggests that observed gender differences may partly reflect differential access to financial information rather than innate preferences, an important distinction for policy implications. Formal gender moderation was tested in five studies (Papadovasilaki et al., 2018; Sachdeva & Lehal, 2024; Kumar et al., 2023; Israel et al., 2019; Bartholomae et al., 2019), with mixed results.

3.3.2. Age

Age was examined in 42 studies. Younger investors (predominantly Gen Z and Millennials) showed higher overconfidence (24 studies), greater impulsivity, and stronger herding tendencies, patterns amplified by social media exposure and online trading platforms (Syukur et al., 2025; R. Chandra et al., 2025). Older investors showed greater loss aversion (19 studies) and risk aversion, consistent with a shift toward capital preservation as the investment horizon shortens and wealth accumulation approaches goals.

An important nuance emerging from this review is the non-linear relationship between age and bias. Moderate-aged investors (roughly 35–55 years) in several studies showed the most balanced risk-taking behavior and best investment performance (Hafez, 2021; Bateman et al., 2011). Older investors with extended experience were more likely to exhibit confirmation bias and status quo effects, representing a qualitative shift in bias type rather than a reduction in irrationality.

A key contradiction: the direction of the age-literacy relationship reversed across cultural contexts. Kumar et al. (2023) found that older investors had superior financial literacy in South Asian contexts, consistent with experience-driven learning. However, Walia and Kiran (2012) and studies from digital-access-enabled contexts found younger cohorts demonstrating higher financial literacy, a pattern consistent with the digital native advantage. These opposing patterns suggest that age effects on bias are mediated by access to financial information, which varies by technology penetration and educational infrastructure.

Syukur et al. (2025) provide the review's most methodologically rigorous evidence on age and bias, using a multi-group PLS-SEM with 1293 participants across Gen X, Gen Y, and Gen Z. Investment experience moderated the herding effect significantly for Gen X ($\beta = -0.059$, $p < 0.001$) but not for Gen Y or Gen Z, suggesting that experience-based learning operates differently across generational cohorts.

3.3.3. Financial Literacy

Financial literacy was the most analytically complex demographic dimension, appearing in 43 studies. Its role is multifaceted and context-dependent, functioning variously as a predictor, mediator, and moderator, and sometimes producing paradoxical effects.

At low levels, financial literacy was consistently associated with stronger herding, greater availability bias, and more impulsive decision-making (21 studies). This relationship was strongest and most consistent in emerging-market contexts (Rasool & Ullah, 2020; Khatik et al., 2021; Sabir et al., 2019). At high levels, financial literacy reduced most biases and improved investment decision quality (22 studies), supporting the theoretical prediction that informed investors are better calibrated (Lusardi & Mitchell, 2014; Agarwal et al., 2025; Hamurcu et al., 2025).

The most theoretically interesting finding, and the most important contradiction in this literature, is the positive relationship between financial literacy and overconfidence in some contexts. Wang and Zou (2024), using a large UK sample ($n = 2000$), found that higher financial literacy was positively associated with overconfidence ($\beta = 0.19$, $p < 0.001$). Murhadi et al. (2024) found a similar pattern in Indonesia. This is consistent with the Dunning–Kruger dynamic: partial knowledge breeds confidence that exceeds competence, while truly high expertise eventually calibrates confidence downward. The implication is that financial literacy interventions may have non-linear effects, while initial literacy improvements could paradoxically increase overconfidence before eventually reducing it.

Regarding formal moderation, eight studies tested financial literacy as a formal moderator. The results were mixed. Ahmad and Shah (2022) found that financial literacy buffered overconfidence-to-investment-decision and overconfidence-to-performance links (both $p < 0.05$). Sabir et al. (2019) found that financial literacy amplified the overconfidence–herding relationship while buffering the experience–herding link. Kulkarni et al. (2025) found that financial literacy significantly intensified the negative effects of both loss aversion and overconfidence on robo-advisor decisions ($OB \times FL$: $\beta = -0.529$, $p < 0.001$). In contrast, Mahmood et al. (2024) found no significant moderation for six biases (all $p > 0.20$). This heterogeneity reflects genuine complexity: financial literacy's moderating role depends on the specific bias, the investment context, and the level and type of literacy measured.

3.3.4. Investment Experience

Investment experience appeared in 34 studies. Like age, its relationship with bias is non-linear. Novice investors show higher overconfidence, greater herding, and more reliance on social cues and recency, a pattern documented consistently across emerging (Djuachiriaty et al., 2024; Almansour et al., 2025) and developed markets (Weiss-Cohen et al., 2022; Safford et al., 2018). Moderate experience (approximately 5–10 years) was associated with improved decision quality and balanced risk-taking in several studies (Hafez, 2021; Bateman et al., 2011).

However, high experience does not guarantee rationality. Experienced investors in multiple studies showed stronger disposition effects and confirmation bias, suggesting that extensive experience reinforces established heuristics and cognitive commitments rather than eliminating them (Shefrin & Statman, 1985). Murhadi et al. (2024) found a positive relationship between investment experience and herding, suggesting that past success creates overconfidence that feeds information-cascade behavior.

The most rigorous moderation evidence comes from Syukur et al. (2025), who found that investment experience moderated the herding-to-decision-making relationship significantly for Gen X ($\beta = -0.059$, $p < 0.001$, using multi-group PLS-SEM with 1293 participants) but not for Gen Y or Gen Z. Safford et al. (2018) showed in a randomized experiment that crash experience reduced stock allocation by approximately 6 percentage points even after controlling for gender, financial literacy, and risk attitude, providing causal evidence for experience effects absent in most survey-based studies.

3.3.5. Income Level

Income appeared in 32 studies, typically as a demographic descriptor rather than a formally modeled predictor. Higher income was associated with lower herding and overconfidence in 14 studies (e.g., Walia & Kiran, 2012; Murhadi et al., 2024), likely mediated by greater financial literacy and access to professional advice. Lower-income investors showed greater susceptibility to availability bias and herding, patterns partly attributable to information deficits and reliance on social networks as information sources.

An important income-specific finding concerns the middle-income bracket, where loss aversion and the disposition effect were most pronounced (Hamurcu et al., 2025; van Dolder & Vandenbroucke, 2024). This is consistent with the theoretical prediction that loss aversion intensifies when wealth preservation is the dominant psychological motive, a pattern more pronounced in the middle-income range than among the very wealthy or very poor. High-income investors in several studies showed value-driven investment tendencies, including preference for ESG and renewable energy investments (Schall, 2020; Hafenstein & Bassen, 2016; Kleffel & Muck, 2024), suggesting that economic surplus enables the expression of psychological and ethical preferences in investment choices.

Income was non-significant in seven studies after controlling for financial literacy and education, suggesting that part of the income effect is mediated through these variables. This has methodological implications: studies that do not include financial literacy alongside income may overestimate income's direct effect.

3.4. Formal Moderation Analyses: Consolidated Evidence

Fourteen studies in the final sample conducted formal moderation or interaction analyses (Table 8). This section synthesizes their findings, with attention given to moderator type, direction, and statistical robustness.

Table 8. Formal moderation analyses: summary of interaction-term and MGA studies.

Study	Country	Moderator	IV (Bias/Construct)	DV	Outcome
Ahmad and Shah (2022)	Pakistan	Financial literacy	Overconfidence	Investment decision and performance	Significant: FL buffered overconfidence → decision ($\beta = 0.29$, $p < 0.05$); FL buffered overconfidence → performance ($\beta = 0.37$, $p < 0.01$)
Sabir et al. (2019)	Pakistan	Financial literacy	Overconfidence; herding behavior; past investment experience	Investment decision	Significant: FL amplified overconfidence → herding ($\beta = 0.186$, $p < 0.01$); FL buffered experience → herding ($\beta = -0.157$, $p < 0.05$)
Tomar et al. (2021)	India	Financial literacy (high vs. low MGA)	Future time perspective; retirement goal clarity	Retirement planning behavior	Significant path differences by FL group: FTP → attitude (diff = 0.20, $p = 0.007$); RGC → RPB (diff = 0.22, $p = 0.010$)
Kulkarni et al. (2025)	India	Financial literacy	Loss aversion; overconfidence	Robo-advisor decision-making	Significant: LA × FL ($\beta = -0.267$, $p < 0.001$); OB × FL ($\beta = -0.529$, $p < 0.001$), both biases amplified by FL in robo-advisor context
Darwish (2025)	Palestine	Financial literacy	Overconfidence	Investment decision quality	Significant: FL × overconfidence strengthened FL → decision quality relationship
Gopal et al. (2025)	India	Household decision-making power	Risk perception	Actual risk-taking behavior	Significant: decision power × risk perception buffered ($\beta = -1.563$, $p < 0.05$)
Syukur et al. (2025)	Indonesia	Investment experience (by generation)	Herding behavior	Investment decision-making	Significant for Gen X ($\beta = -0.059$, $p < 0.001$); non-significant for Gen Y and Gen Z
Israel et al. (2019)	Israel	Gender × music group × subjective music evaluation	Music-induced mood/affect; naïve diversification/1-n heuristic	Risk-taking behavior (lottery investment); portfolio diversification	Significant: gender × music × subjective evaluation triple interaction ($F = 4.553$, $p = 0.034$); Gender × music non-significant (lottery $p = 0.109$, portfolio $p = 0.253$)
Papadovasilaki et al. (2018)	United States	Gender	Crash experience	Asset allocation to risky stocks	Significant: early crash effect stronger for males; gender × Down_Aftershock significant at 1% in OLS/FRM
Putri Pa et al. (2022)	Indonesia	Polygamy risk (social/marital risk)	Financial literacy; risk tolerance	Investment decision (short vs. long term)	Significant: FL × polygamy ($F = 56.878$, $p < 0.001$); RT × polygamy ($F = 54.741$, $p < 0.001$)

Table 8. Cont.

Study	Country	Moderator	IV (Bias/Construct)	DV	Outcome
Mahmood et al. (2024)	Pakistan	Financial literacy	6 biases (anchoring, overconfidence, disposition, herding, risk aversion, represen- tativeness)	Investment decision-making	Non-significant: all FL moderation paths $p > 0.20$; biases directly significant but FL did not moderate them
Sachdeva and Lehal (2024)	India	Gender (multi-group SEM)	Contextual factors (firm image, accounting info, neutral info, advocate rec., personal financial needs)	Investment decision-making	Non-significant: gender did not moderate any contextual factor $\rightarrow$ investment decision relationship
Kumar et al. (2023)	India	Gender (MGA)	Digital FL; financial capability; impulsivity	Financial decision-making	Non-significant gender MGA differences; impulsivity significantly weakened FC $\rightarrow$ FDM (FC $\times$ IMP $\beta = -0.070$, $p <$ 0.05)
Bartholomae et al. (2019)	United States	Gender $\times$ attribute frames; education $\times$ attribute frames	Framing (gain/loss/ aspirational)	Wise-to-borrow; amount-to-borrow	Mostly non-significant; gender $\times$ education $\times$ frames significant for amount-to-borrow ($F = 1.585$, $p = 0.045$)

Financial literacy was the most commonly tested moderator (tested in 8 of the 14 studies), with results ranging from strong significant buffering effects ([Ahmad & Shah, 2022](#); [Kulkarni et al., 2025](#); [Sabir et al., 2019](#)) to complete non-significance ([Mahmood et al., 2024](#)). The direction of financial literacy moderation also varied: in most studies it buffered bias effects, but [Sabir et al. \(2019\)](#) found that it amplified the overconfidence–herding relationship, consistent with the paradox identified in Section 3.3.3.

Gender was tested as a formal moderator in five studies. [Papadovasilaki et al. \(2018\)](#) found that early crash experience had a significantly stronger effect on males than females ($p < 0.01$). [Israel et al. \(2019\)](#) found a three-way interaction between music group, gender, and subjective music evaluation for diversification behavior ($F = 4.553$, $p = 0.034$). However, [Sachdeva and Lehal \(2024\)](#), [Kumar et al. \(2023\)](#), and [Bartholomae et al. \(2019\)](#) found gender moderation to be largely non-significant, suggesting that gender’s influence may be more pronounced in experimental settings than in real-world survey data.

Investment experience moderated herding behavior in [Syukur et al. \(2025\)](#) with a heterogeneous generational pattern. Social risk (specifically, polygamy risk as a proxy for marital instability) significantly moderated both financial literacy and risk tolerance effects on investment allocation in [Putri Pa et al. \(2022\)](#), a novel finding suggesting that institutional and social risk contexts can override individual financial knowledge.

3.5. Thematic Synthesis

Drawing across all 57 studies, four overarching themes emerge that synthesize the behavioral and demographic evidence at a level beyond frequency tabulation.

Theme 1. *Financial Literacy as a Non-Linear and Context-Dependent Moderator.*

The most widespread and theoretically significant conclusion from this review is that financial literacy does not directly reduce behavioral biases. It works in a non-linear, context-specific and bias-specific way. Financial literacy is always associated with a decrease in herding and availability bias at low levels. At moderate levels, it can lead to overconfidence, as is consistent with the Dunning–Kruger effect and is well documented by Wang and Zou (2024) and Murhadi et al. (2024). Most biases are diminished at high levels, but overconfidence might remain with the highly confident experts. The non-linear nature has a critical implication for financial literacy interventions, as financial literacy programs that increase awareness but do not lead to the development of deep competence could result in an increase in overconfidence and its associated costs.

Theme 2. *Gender Differences Are Real but Partially Socially Constructed.*

The evidence for gender differences in behavioral biases is robust across multiple high-quality studies, with males showing greater overconfidence and risk-taking and females showing greater risk aversion and loss aversion. However, the observation from Döbeli and Vanini (2010) that simplified product communication eliminated the gender gap in structured-product uptake, combined with evidence that gender effects disappear after controlling for financial literacy (Kumar et al., 2023; Sachdeva & Lehal, 2024), suggests that gender differences in investment behavior are partly mediated by differential access to financial information and cultural norms regarding financial agency. This has important policy implications: targeting financial literacy programs toward women may be more effective than assuming that gender represents an immutable behavioral boundary.

Theme 3. *Context Moderates Everything.*

In nearly every relationship between demographics and behavioral biases, context is important. The direction and magnitude of the effects depend on the level of market development (emerging markets vs. developed markets), penetration of the technology and digital access, financial decision-making and financial norms of men and women, institutional quality and investor protection, and the specific investment product or decision being analyzed. The literature is concentrated in emerging markets in South Asia and Southeast Asia, and the sample consists of about 53% from India, Pakistan, Indonesia, and Malaysia, so many results may not be applicable to developed markets, North American markets, East Asian markets or Sub-Saharan African markets. This is an important geographical limitation to the field that needs to be rectified in the future.

4. Discussion

This review combines the findings of 57 quality-assessed empirical studies to offer a comprehensive PRISMA-based analysis of the influence of demographic characteristics on behavioral biases in investment decision-making. There are some observations that demand further comment.

4.1. Reconciling Contradictions in the Financial Literacy–Overconfidence Relationship

Financial literacy and overconfidence are positively associated in the UK (Wang & Zou, 2024) and Indonesia (Murhadi et al., 2024), which seems counterintuitive to what many would expect: a negative association between financial literacy and bias. There are two mechanisms that provide some reconciliation. The Dunning–Kruger explanation is that investors who have advanced from “no knowledge” to “moderate knowledge” are more likely to view their competence as greater than it truly is, based on their level of calibration. Second is the selection explanation: investors who are more financially literate are more likely to be active investors in the financial markets, and this is related to overconfidence (Barber & Odean, 2001). These mechanisms are not mutually exclusive, and

can both account for the paradox. Future research employing longitudinal designs might examine the possibility that the positive literacy–overconfidence relationship represents a developmental stage that reverses at high levels of literacy.

4.2. Geographic and Cultural Heterogeneity

It is difficult to generalize because of the geographic focus of this literature in South and Southeast Asian emerging markets. Some institutional characteristics of the markets in India, Pakistan, Indonesia and Malaysia may differ from North America, Europe and East Asia and influence investor behavior, such as how investors are protected as retail investors, the degree of maturity of the stock market, cultural attitudes to risk and authority, and the informal social network involvement in financial decision-making. Due to the scarcity of developed-market studies in this review (Bateman et al., 2011; van Dolder & Vandenbroucke, 2024; Döbeli & Vanini, 2010; Kleffel & Muck, 2024), some of these studies yield strikingly different patterns, further underscoring the need to include geographically diverse future studies.

4.3. Practical Implications

The identified thematic patterns have concrete implications for three groups of stakeholders. The evidence supports a demographic approach to investing: for financial advisors and wealth managers, overconfident young male novice investors will need to have their overconfidence corrected, whereas older female conservative investors may benefit from some framing around loss avoidance and goal certainty. For policy makers and financial regulators, financial literacy disclosures should be tailored to literacy level, with special attention given to interventions for intermediately literate investors who are especially susceptible to overconfidence. Regulators could consider product-specific literacy thresholds for high-risk investment products. For financial educators, financial education programs need to go beyond awareness of financial competency development, making sure to tackle the overconfidence trap linked to partial knowledge.

4.4. Limitations of This Review

This review has several important limitations that should inform the interpretation of the findings and the design of future research.

First, the search was restricted to the Scopus database. While Scopus provides broad coverage of peer-reviewed behavioral finance research, studies indexed only in Web of Science, PsycINFO, SSRN, or Google Scholar may have been missed. The addition of a second database in future updates would reduce this selection risk.

Second, 49 records (37% of the screened sample) could not be retrieved for full-text assessment, primarily due to institutional access limitation. Some relevant studies may have been excluded as a result.

Third, although a formal quality appraisal was conducted, this review did not perform a quantitative meta-analysis due to the extreme heterogeneity in bias operationalization, demographic measurement, and statistical reporting across studies. Effect sizes are not directly comparable across studies reporting regression coefficients, ANOVA F-statistics, OR from logistic regression, and SEM path coefficients, making pooled effect estimation unreliable without individual study data.

Fourth, the geographic distribution of included studies is heavily weighted toward South and Southeast Asian emerging markets. Conclusions about financial literacy moderation, gender effects, and experience effects may not generalize to Western developed markets or other cultural contexts.

Fifth, the absence of longitudinal studies prevents causal inference about the direction of demographic-biased relationships. Cross-sectional correlations, which dominate this

literature, cannot distinguish whether financial literacy reduces bias or whether less-biased investors seek out financial knowledge.

5. Conclusions

Several conclusions are supported across the evidence base. Overconfidence and herding are the two most prevalent behavioral biases, predominantly affecting younger, male, and less experienced investors. Loss aversion and risk aversion are more consistently observed among older, female, and financially insecure investors, consistent with prospect theory predictions. Financial literacy is the most important demographic moderator, but its effect is non-linear: low literacy amplifies herding and impulsive decisions, moderate literacy may paradoxically amplify overconfidence, and high literacy generally reduces most biases. Investment experience transforms rather than eliminates bias, shifting the dominant bias type from social-influence-driven to commitment-driven patterns.

Among the 14 studies that conducted formal moderation analyses, financial literacy was the most frequently supported moderator, though with important heterogeneity in direction and magnitude. The finding that gender differences largely disappear after controlling financial literacy and that simplified communication eliminated gender gaps in product uptake suggests that the gender bias relationship is partially mediated by information access rather than fixed preference.

Future research priorities emerging from this review include (1) longitudinal experimental designs capable of establishing causal direction; (2) studies from North America, East Asia, and Sub-Saharan Africa to address geographic imbalance; (3) intersectionality analyses examining how multiple demographic variables jointly moderate bias; (4) pre-registered interaction-term moderation models to move beyond subgroup comparisons; and (5) replication studies in developed-market contexts to test the generalizability of emerging-market findings.

The behavioral heterogeneity of investors documented in this review has a clear practical implication: behavioral finance interventions, whether financial literacy programs, regulatory disclosures, or advisory services, must be designed with demographic specificity. A universal approach to investor protection and education will systematically underserve the investors who are most vulnerable to cognitive and emotional bias.

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Abbreviations

The following abbreviations are used in this manuscript:

AMOS	Analysis of Moment Structures
ANOVA	Analysis of Variance
CFA	Confirmatory Factor Analysis
CM	Clearly Met
DV	Dependent Variable
EFA	Exploratory Factor Analysis
EMH	Efficient Market Hypothesis
ESG	Environmental, Social, and Governance
EUT	Expected Utility Theory
F	F-statistic
FC	Financial Capability
FDM	Financial Decision-Making
FL	Financial Literacy
FTP	Future Time Perspective
Gen X/Y/Z	Generation X/Y/Z
GLS	Generalized Least Squares
IMP	Impulsivity
IV	Independent Variable
KMO	Kaiser–Meyer–Olkin
LA	Loss Aversion
MANOVA	Multivariate Analysis of Variance
MGA	Multi-Group Analysis
MICOM	Measurement Invariance of Composite Models
MMAT	Mixed-Methods Appraisal Tool
NR	Not Reported
OB	Overconfidence Bias
OLS	Ordinary Least Squares
OR	Odds Ratio
p	Probability value (significance level)
PLS-SEM	Partial Least Squares Structural Equation Modeling
PM	Partially Met
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
Q1–Q8	Quality Criteria 1 through 8
R^2	Coefficient of Determination
RPB	Retirement Planning Behavior
RGC	Retirement Goal Clarity
SEM	Structural Equation Modeling
SRI	Socially Responsible Investment
SPSS	Statistical Package for the Social Sciences
WTP	Willingness to Pay
β	Standardized Regression Coefficient

Appendix A

Table A1. Summary of all 57 included studies.

Study (Author, Year)	Country	n	Method	Behavioral Constructs	Demographic Variables
(Nga & Ken Yien, 2013)	Malaysia	314	Cross-sectional survey; regression; <i>t</i> -tests	Risk aversion; cognitive bias; SRI	Gender; education (course major)
(Döbeli & Vanini, 2010)	Switzerland	68	Mixed design; field experiment; prospect theory estimation	Risk aversion; loss aversion; framing; hypothetical bias	Gender; age; income/rank; investment experience
(Walia & Kiran, 2012)	India	400	Cross-sectional survey; chi-square; ANOVA; regression	Risk perception; disclosure risk	Gender; age; knowledge; income; marital status
(Lim et al., 2020)	Malaysia	492	Cross-sectional survey; SEM (AMOS)	Risk perception; subjective knowledge; overconfidence-like	Gender; age; education; financial literacy; income
(Bateman et al., 2011)	Australia	818–919	Repeated choice experiment; latent class model	Risk tolerance; crisis salience; mean variance consistency	Gender; age; education; income; investment experience
(A. Chandra et al., 2017)	India	230	Cross-sectional survey; <i>t</i> -tests; binary regression; OLS	Self-perceived confidence; trading behavior	Gender; age; education; income; portfolio size
(Jamaludin & Gerrans, 2015)	Malaysia	439	Cross-sectional survey; binary logistic regression	Financial risk tolerance; advisor influence	Gender; age; education; financial knowledge; income; religion
(McCannon & Peterson, 2015)	United States	146	Laboratory experiment; OLS; probit; fixed effects	Trusting investment behavior; reciprocity	Gender; finance education; freshman status
(Raut, 2020)	India	390	EFA; CFA; SEM; mediation analysis	Past behavior bias; attitude	Gender; age; education; financial literacy; investment experience
(Bartholomae et al., 2019)	United States	1926	Experimental survey; two-way/three-way ANOVA	Framing effects; gain/loss frames	Gender; age; education
(Linge et al., 2024)	India	409	Cross-sectional survey; multiple regression; MANOVA	Risk attitude; risky asset holding; investor happiness	Gender; age; education; income; family size

Table A1. Cont.

Study (Author, Year)	Country	n	Method	Behavioral Constructs	Demographic Variables
(Papadovasilaki et al., 2018)	United States	N/A	Laboratory experiment; OLS; GLS; fractional response models	Loss aversion; experience effects; crash experience	Gender; investment experience
(Kleffel & Muck, 2024)	Germany	346	Stated-choice experiment; mixed logit; WTP estimation	Affect heuristic; sustainability label bias	Gender; age; education; financial literacy; income
(Prakash & Alagarsamy, 2022)	India	163	Simulation study; ANOVA; OLS regression	Gender-linked trading aggressiveness; overconfidence	Gender; age; education; family income
(Budsaratragoon et al., 2015)	Thailand	176 + 77	Pension allocation simulation; chi-square; regressions	Home bias; risk aversion; framing; financial expertise	Gender; age; education; financial expertise; marital status
(Israel et al., 2019)	Israel	367	Laboratory experiment; mixed-design ANOVA; <i>t</i> -tests	Naïve diversification; risk-taking; mood/affect	Gender; age; education
(Tomar et al., 2021)	India	485	Cross-sectional survey; PLS-SEM; multi-group analysis	Retirement planning; risk tolerance	Gender; age; education; financial literacy; income
(Strydom et al., 2018)	Australia	350	Experimental survey; pre/post tests; <i>t</i> -tests by mood/gender	Belief perseverance; earnings-forecast reactions	Gender; age; education; native language
(Khawaja & Alharbi, 2021)	Saudi Arabia	125	Cross-sectional survey; correlation; regression; ANOVA	Investor behavior factors; past performance; firm reputation	Gender; age; education; professional experience; investment volume
(Renerte et al., 2023)	Germany	160	Randomized laboratory experiment; OLS; probit models	Overconfidence; overinvestment; group investment decisions	Gender; age; education; numeracy; Big Five
(Djuachiriaty et al., 2024)	Indonesia	176	Explanatory quantitative; PLS-SEM	Investment feasibility; overconfidence; herding; regret aversion; risk tolerance	Gender; age; education; civil-service rank
(Oehler et al., 2018)	Germany	364	Experimental asset-market study; Spearman/Kendall; OLS; Tobit	Extraversion; neuroticism; risky-asset holdings; overpricing	Gender; age; personality traits
(Ahmad & Shah, 2022)	Pakistan	183	Cross-sectional survey; hierarchical regression; PROCESS; SEM	Overconfidence; risk perception; investment decision	Gender; age; education; financial literacy; investment experience

Table A1. Cont.

Study (Author, Year)	Country	n	Method	Behavioral Constructs	Demographic Variables
(Kumar et al., 2023)	India	634	Cross-sectional survey; PLS-SEM; MICOM; multi-group analysis	Impulsivity; financial decision-making	Gender; age; education; digital financial literacy
(R et al., 2025)	India	550	Cross-sectional survey; PLS-SEM mediation	Rational/irrational factors; overconfidence; anchoring; availability; information cascade	Gender; age; education; investment experience; occupation
(Ladrón de Guevara Cortés et al., 2023)	Argentina	620	Experimental survey; Kruskal–Wallis; Mann–Whitney U	Prospect-theory decision patterns; certainty effect; reflection effect	Gender; education; semester; university type
(Uma & Maheswari, 2025)	India	284	Mixed-method; regression; ANOVA; chi-square; NVivo	Overconfidence; herding; heuristics; loss aversion	Gender; age; education; financial literacy; income; occupation
(Srivastava et al., 2025)	India	196	Cross-sectional survey; linear regression; SPSS version 22	Anchoring; herding; loss aversion; stock-market decision-making	Gender (all women); age; investment experience; income
(Nga, 2020)	Malaysia	463	Cross-sectional survey; PLS-SEM; bootstrapping	Herding; risk aversion; kiasuism	Gender; age; financial knowledge
(Rad et al., 2025)	Romania	548	Online survey; decision-tree regression; predictive modeling	Behavioral/attitudinal investment predictors; AI trust	Gender; age; education; financial education; investment experience
(Metawa et al., 2019)	Egypt	384	Cross-sectional survey; partial multiple regression; path analysis	Investor sentiment; overconfidence; overreaction; herding	Gender; age; education; investment experience
(Wahba et al., 2025)	Egypt	300	Cross-sectional survey; OLS regression; reliability testing	Availability; overconfidence; gambler's fallacy; loss aversion; regret aversion	Gender; age; education; investment experience
(Sachdeva & Lehal, 2024)	India	402	Cross-sectional survey; AMOS CFA/SEM; multi-group analysis by gender	Firm image; accounting information; contextual investor-information factors	Gender; age; education; financial education; investment experience
(R. Chandra et al., 2025)	Indonesia	528	Cross-sectional survey; PLS-SEM; moderation analysis	Cognitive biases; sentiment; crypto reinvestment intention	Age; education; financial literacy; crypto-investor status

Table A1. Cont.

Study (Author, Year)	Country	n	Method	Behavioral Constructs	Demographic Variables
(Okumura et al., 2023)	Brazil	224	Experimental questionnaire; Fisher's exact; ANOVA	Decoy effect; attraction effect; stock investment choice	Gender; age; education; professional experience
(Almansour et al., 2025)	Saudi Arabia	315	Cross-sectional survey; SEM; reliability testing	Herding; disposition effect; overconfidence; risk perception	Gender; age; education; financial literacy; investment experience
(Weiss-Cohen et al., 2022)	United Kingdom	1600	Preregistered repeated-choice experiments; mixed-effects modeling	Past-performance chasing; return extrapolation; disclaimer effect	Gender; age
(Schall, 2020)	Germany	806	Cross-sectional online survey; logistic regressions; factor analysis	Renewable-energy participation; pro-environmental identity; psychic return	Gender; age; education; income; marital status; children; homeownership
(Darwish, 2025)	Palestine	146	Cross-sectional survey; EFA; regression; moderation analysis	Overconfidence; investment decision quality	Gender; age; education; financial literacy; investment experience
(Safford et al., 2018)	United States	78	2 × 2 between-subject experiment; repeated-measures ANOVA; OLS	Crash-experience effect; myopic loss aversion; belief updating	Gender; age; financial literacy; investment experience; risk attitude
(Agarwal et al., 2025)	India	482	Cross-sectional survey; SEM; mediation analysis	Self-attribution; overconfidence; herding; disposition; anchoring	Gender; age; education; financial literacy; investment experience; income
(Hamurcu et al., 2025)	Türkiye	703	Cross-sectional survey; SEM; ANOVA; path analysis	Risk tolerance; behavioral portfolio decision-making	Gender; age; education; financial literacy; mutual-fund investor status; income
(Putri Pa et al., 2022)	Indonesia	329	Cross-sectional survey; MANOVA	Risk tolerance; financial literacy; polygamy risk; regret aversion	Gender; age; financial literacy; income; marital status
(Murhadi et al., 2024)	Indonesia	170	Cross-sectional survey; SEM; path testing	Overconfidence; disposition effect; herding	Gender; age; education; financial literacy; investment experience; income
(Raghu et al., 2025)	India	300	Quantitative survey; EFA; KMO; Bartlett's test; Varimax rotation	Investment confidence; behavioral biases; risk aversion; social-cognitive framing	Financial literacy; gender; age; education; investment experience

Table A1. Cont.

Study (Author, Year)	Country	n	Method	Behavioral Constructs	Demographic Variables
(Rasool & Ullah, 2020)	Pakistan	300	Cross-sectional survey; ordinal regression; EFA; ANOVA	Representativeness; overconfidence; anchoring	Gender; age; education; financial literacy; income
(van Dolder & Vandenbroucke, 2024)	Belgium	1040–3740	Field implementation; behavioral risk profiling; Kruskal–Wallis; correlation	Loss aversion; risk aversion; behavioral risk profiling	Gender; age; education; financial literacy; income
(Hafenstein & Bassen, 2016)	Germany	371	Online cross-sectional survey; CFA; SEM; mediation testing	Affect heuristic; mental framing; information overload; SRI decision-making	Gender; age; education; investment experience; income
(Khatik et al., 2021)	India	404	Cross-sectional survey; PLS-SEM; bootstrapping	Social media influence; Gen Z community behavior	Gender; age; education; financial literacy
(Gopal et al., 2025)	India	312	Cross-sectional survey; OLS regression; mediation/moderation bootstrapping	Risk-taking behavior; risk perception; overconfidence; household decision-making power	Gender; age; education; financial literacy; investment experience; income
(Khilar & Singh, 2019)	India	91	Cross-sectional survey; descriptive statistics; correlation matrix	Overconfidence; media-response bias; disposition effect; loss aversion	Gender; age; education; investment experience; income
(Sabir et al., 2019)	Pakistan	340	Cross-sectional survey; PLS-SEM; bootstrapping; moderation analysis	Overconfidence; herding behavior; investment experience	Gender; age; education; financial literacy; investment experience
(Syukur et al., 2025)	Indonesia	1293	Cross-sectional survey; multi-group PLS-SEM; moderation analysis	Herding behavior; investment experience; generational decision-making	Age/generation; education; investment experience; income
(Hafez, 2021)	Egypt	245	Cross-sectional survey; regression; before/after pandemic comparison	Loss aversion; regret aversion; disposition; overconfidence; herding; gambler's fallacy	Gender; age; education; investment experience; income; portfolio size
(Wang & Zou, 2024)	United Kingdom	2000	Online survey; hierarchical regression; mediation analysis; bootstrapping	Availability bias; herding; overconfidence; confirmation bias; anchoring	Gender; age; education; financial literacy; investment experience

Table A1. Cont.

Study (Author, Year)	Country	n	Method	Behavioral Constructs	Demographic Variables
(Kulkarni et al., 2025)	India	461	Cross-sectional survey; PLS-SEM with moderation; SmartPLS 4.0	Loss aversion; overconfidence; robo-advisor decision-making	Gender; age; education; financial literacy; investment experience; income
(Mahmood et al., 2024)	Pakistan	261	Cross-sectional survey; hierarchical regression; PROCESS macro moderation	Anchoring; overconfidence; disposition; herding; risk aversion; representativeness	Gender; age; education; financial literacy; investment experience

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