The Causal Relationship between Managers' and Investors' Cognitive Biases and the Performance of the Iranian Stock Market: A Mixed-Methods Approach

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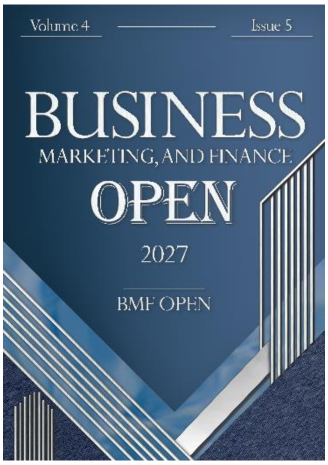

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Citation: Shakeri, J., Heydari, M., & Baradaran Hasanzadeh, R. (2027). The Causal Relationship between Managers' and Investors' Cognitive Biases and the Performance of the Iranian Stock Market: A Mixed-Methods Approach. *Business, Marketing, and Finance Open*, 4(5), 1-25.

Received: 13 April 2026
Revised: 18 July 2026
Accepted: 26 July 2026
Initial Publication: 28 July 2026
Final Publication: 01 September 2027

Abstract: This study aimed to develop and test a causal model explaining the relationships among managers' and investors' cognitive biases, decision-making quality, artificial intelligence-based bias-reduction mechanisms, and the performance of the Iranian stock market. This developmental study used a qualitative-dominant sequential exploratory mixed-methods design. In the qualitative phase, 12 university professors, behavioral-finance researchers, market analysts, managers, and experienced investors were selected purposively and interviewed through in-depth semi-structured interviews until thematic saturation. The interview data were analyzed through thematic analysis using MAXQDA, and the extracted dimensions and indicators were refined through a Delphi process. In the quantitative phase, 200 managers, investors, financial analysts, consultants, and decision-makers active in the Iranian capital market were selected through random sampling. Data were collected using a researcher-developed questionnaire derived from the qualitative findings. Reliability and validity were examined using Cronbach's alpha, composite reliability, and average variance extracted. Structural relationships were tested using structural equation modeling and bootstrapping. Fundamental cognitive biases significantly reduced decision-making quality ($\beta = -0.42$, $t = 5.25$, $p < 0.001$). Investment and financial biases ($\beta = -0.40$, $t = 4.44$, $p < 0.001$), informational and analytical biases ($\beta = -0.31$, $t = 3.88$, $p < 0.001$), narrative biases ($\beta = -0.28$, $t = 3.11$, $p = 0.002$), organizational and cultural biases ($\beta = -0.25$, $t = 3.57$, $p < 0.001$), and bias-related consequences ($\beta = -0.29$, $t = 3.63$, $p < 0.001$) also had significant negative effects. Artificial intelligence applications had the strongest positive effect on decision-making quality ($\beta = 0.46$, $t = 5.75$, $p < 0.001$), followed by advanced artificial-intelligence mechanisms ($\beta = 0.38$, $t = 5.43$, $p < 0.001$), bias-reduction strategies ($\beta = 0.36$, $t = 5.14$, $p < 0.001$), institutional strategies ($\beta = 0.32$, $t = 4.57$, $p < 0.001$), and organizational learning ($\beta = 0.27$, $t = 3.38$, $p = 0.001$). Decision-making quality significantly improved stock-market performance ($\beta = 0.64$, $t = 9.21$, $p < 0.001$). Cognitive biases impair managerial and investment decision-making and indirectly weaken stock-market performance, whereas artificial intelligence, systematic debiasing, institutional controls, and organizational learning improve decision quality and market outcomes.

Keywords: Cognitive Biases; Investor Behavior; Managerial Decision-Making; Artificial Intelligence; Behavioral Finance; Stock-Market Performance; Iranian Stock Market; Mixed Methods

1. Introduction

Stock markets play a central role in mobilizing savings, allocating capital, pricing financial assets, and directing resources toward productive economic activities. Classical financial theories generally assume that market participants evaluate available information rationally, estimate risk and return consistently, and select alternatives that maximize expected utility. Under this assumption, security prices should incorporate relevant information, and deviations from fundamental value should be corrected through rational trading. However, actual market behavior repeatedly demonstrates patterns that cannot be explained exclusively through rational expectations, informational efficiency, or conventional risk–return models. Investors frequently retain losing assets, imitate the behavior of others, overreact to recent news, underestimate uncertainty, and assign excessive weight to their own judgments. Managers may similarly persist with unsuccessful strategies, selectively interpret accounting and market information, and overestimate their ability to predict or control future outcomes. Behavioral finance emerged in response to these limitations by integrating psychological, social, and cognitive explanations into the analysis of financial decision-making and market performance [1-3].

Behavioral finance does not reject the importance of economic incentives, information, and institutional structures; rather, it argues that these factors are interpreted through bounded human cognition. Financial decisions are made under conditions of incomplete information, uncertainty, time pressure, emotional arousal, social influence, and limited computational capacity. In these circumstances, individuals use heuristics and simplified mental rules to reduce complexity. Such shortcuts can facilitate rapid judgment, but they may also generate systematic and predictable errors known as cognitive biases. These biases affect how information is noticed, retrieved, framed, evaluated, and translated into action. Their effects are not restricted to inexperienced retail investors. Reviews of professional decision-making indicate that specialists, managers, advisers, and other occupational groups remain vulnerable to cognitive distortions despite their knowledge and experience [4]. Recent systematic and meta-analytic evidence further suggests that behavioral biases have substantial and recurring effects on investment choices and financial performance across different populations, markets, and methodological settings [5, 6].

Among the most widely examined biases in financial markets is overconfidence. Overconfident decision-makers overestimate the precision of their knowledge, the accuracy of their forecasts, and their ability to identify profitable opportunities. They may underestimate the probability of error, trade excessively, neglect contradictory evidence, and construct portfolios that are insufficiently diversified. Systematic reviews show that overconfidence is closely associated with excessive trading, inappropriate risk-taking, and distorted investment judgment among both retail and professional investors [7-9]. Personality characteristics may intensify or weaken such tendencies because traits related to confidence, openness, emotional stability, and risk tolerance influence how investors respond to uncertainty and market signals [10]. In institutional settings, overconfidence may also affect managers' expected returns, strategic forecasts, financing policies, and interpretations of company performance. Evidence from the Tehran Stock Exchange indicates that investors' behavior is related to managers' return expectations, suggesting that managerial beliefs and investor sentiment may interact in shaping market outcomes [11].

The illusion of control is closely related to overconfidence but refers more specifically to the belief that an individual can influence or accurately predict outcomes that are partly or largely determined by chance, complexity, or external forces. Managers and investors affected by this bias may believe that experience, analytical skill, personal networks, or access to selected information allows them to control market conditions. They may therefore underestimate systemic risk, ignore unexpected events, or maintain confidence in inaccurate forecasts. The illusion of control is particularly relevant in financial environments characterized by volatility and ambiguity because market outcomes emerge from the interaction of numerous economic, political, institutional, and psychological factors that no single actor can fully manage [12]. When combined with managerial authority, this bias can strengthen unilateral decision-making and reduce openness to corrective feedback.

Anchoring and confirmation bias further distort the interpretation of financial information. Anchoring occurs when investors rely excessively on an initial value, reference point, prior price, forecast, or expectation and adjust insufficiently when new evidence becomes available. Empirical findings indicate that anchoring significantly influences investment decisions, particularly when market participants face uncertainty or lack a clear objective valuation benchmark [13]. Confirmation bias leads individuals to seek, remember, and interpret evidence in ways that support existing beliefs while discounting inconsistent information. Although confirmation bias may serve certain cognitive functions by stabilizing beliefs and reducing decision costs, it can become harmful when decision-makers fail to revise inaccurate expectations [14]. In capital markets, confirmation bias can affect professional forecasts and market pricing. Evidence concerning investment banks indicates that analysts may interpret forecast revisions through prior beliefs, and these biased revisions can subsequently influence market prices [15]. Thus, cognitive bias may enter the pricing process not only through individual investors but also through professional information intermediaries.

Ambiguity aversion constitutes another important dimension of financial judgment. It refers to the tendency to avoid alternatives when probabilities, outcomes, or relevant information are unclear. The extensive literature on ambiguity aversion demonstrates that individuals distinguish between measurable risk and uncertain situations in which probabilities cannot be estimated confidently [16]. In stock markets, ambiguity-averse investors may prefer familiar securities, delay investment, overallocate resources to domestic assets, or reject potentially beneficial opportunities merely because their outcomes are difficult to interpret. Status quo bias similarly encourages individuals to retain existing investments or preserve current portfolio structures even when available evidence supports change. Experimental findings indicate that valuation decisions can differ depending on whether the status quo is framed as a gain or loss, illustrating how reference points affect asset evaluation [17]. These biases may restrict portfolio adjustment and delay the correction of poorly performing positions.

Escalation of commitment represents the tendency to continue allocating resources to a failing decision because of prior investment, personal responsibility, reputational concerns, or reluctance to acknowledge error. In financial and managerial contexts, this bias can lead to the continuation of unsuccessful projects, retention of declining securities, and further investment in strategies that no longer have adequate economic justification. Decision aids that require explicit evaluation of alternatives, opportunity costs, and termination criteria can reduce escalation and support de-escalation from unsuccessful courses of action [18]. This finding is particularly relevant to the present study because it suggests that cognitive bias is not necessarily irreversible; carefully designed analytical procedures and institutional controls can improve judgment.

Herding is another major mechanism through which individual biases become collective market phenomena. Herding occurs when investors follow the actions, opinions, or expectations of others rather than relying on independent analysis. It can arise from informational uncertainty, fear of reputational loss, perceived expertise of other market participants, or fear of missing profitable opportunities. Evidence from emerging markets indicates that herding affects investment management and perceptions of market efficiency [19]. Herding and heuristic biases also influence portfolio construction and performance, demonstrating that collective imitation may alter asset allocation and reduce diversification [20]. Fear of missing out can mediate the relationship between herding, loss aversion, and retail investment behavior by encouraging individuals to enter rising markets or purchase popular securities without sufficient analysis [21]. Mathematical and behavioral models further show that investor behavior can propagate through market networks, producing synchronized reactions and amplifying price movements [22].

Herding is not limited to individual investors. Managers may imitate competitors, dominant firms, industry leaders, or influential institutional investors. Micro-level evidence indicates that both investor herding and managerial herding can influence firm financial performance [23]. Institutional investors may also become embedded in informational echo chambers in which social connections and ideological similarity reinforce common interpretations of financial events [24]. Social attachment and empathy can influence the availability of information in memory, thereby affecting investment judgment and the weight assigned to socially salient experiences [25]. These findings suggest that cognitive biases are socially distributed and may be reinforced through professional networks, organizational communities, online interactions, and shared narratives.

Investor sentiment represents another channel linking psychology to stock returns. Sentiment reflects beliefs and emotions that are not fully justified by fundamental information but nevertheless affect demand for securities. Firm-specific sentiment may influence daily stock returns by shaping buying and selling pressure around particular companies [26]. Sentiment also interacts with ethical perceptions, social attitudes, and the attractiveness of specific investment categories, as demonstrated by research on so-called sin stocks [27]. Time-series momentum and intraday trading behavior likewise show that investors may extrapolate recent price movements and contribute to short-term continuation patterns [28]. Herd behavior and investor sentiment can also interact within professionally managed funds, indicating that collective expectations are relevant even in markets characterized by substantial analytical expertise [29].

The influence of behavioral bias may vary across regions, cultures, market structures, and investor groups. Evidence based on structural equation modeling and measurement-invariance analysis suggests that regional diversity affects the strength and expression of behavioral biases in investment decisions [30]. Research on emerging markets indicates that psychological and social factors may become especially influential when investor protection, disclosure quality, market depth, and informational efficiency are limited [2, 31]. Institutional investors are also affected by behavioral finance mechanisms, despite their access to professional expertise and sophisticated analytical tools [32]. Mixed-method evidence concerning mutual fund investment demonstrates that psychological and behavioral determinants interact with financial considerations, reinforcing the need to combine qualitative exploration with quantitative testing [33]. Scale-development research has similarly shown that investment bias is multidimensional and should be measured through instruments capable of distinguishing among different cognitive tendencies [34].

Within Iran, the behavioral dimensions of investment and managerial decision-making are particularly important because the stock market operates under conditions of economic uncertainty, policy fluctuations, inflationary pressure, changing regulations, and sensitivity to political and international developments. These conditions may increase ambiguity, emotional responses, reliance on informal information, and demand for simplified interpretations. Research concerning portfolio managers in Iran has demonstrated that cognitive abilities and cognitive biases are related to investment performance [35]. Evidence from the Iranian stock market also indicates that accounting biases can influence corporate financial policies, showing that biased judgment may affect not only security selection but also financing, reporting, and managerial policy decisions [36]. Nevertheless, much of the existing research has focused either on investors or managers separately, whereas stock-market performance is likely to reflect their interaction.

The connection between managers' and investors' biases is theoretically significant. Managers generate forecasts, disclose information, select financing strategies, and make operational decisions that influence firm value. Investors interpret these signals and determine market prices through their trading decisions. If managers are overconfident, committed to prior strategies, or selective in their use of information, their corporate decisions and disclosures may deviate from objective conditions. If investors simultaneously display anchoring, confirmation bias, herding, or narrative dependence, they may fail to identify or correct managerial errors. The resulting interaction can contribute to mispricing, excessive volatility, speculative bubbles, inefficient capital allocation, and reduced market confidence. Conversely, independent analysis, transparent reporting, effective governance, and structured decision procedures may weaken the transmission of individual bias to market-level outcomes.

Technological development introduces both opportunities and new risks. Digitalization has transformed financial analysis, trading, portfolio management, reporting, and advisory services. The integration of digital technologies into corporate finance can improve information access, processing speed, monitoring, and coordination [37]. Qualitative research involving financial planners suggests that digitalization can help professionals overcome cognitive biases by making information more visible, standardizing procedures, and supporting systematic comparison of alternatives [38]. Robo-advisers may similarly influence investment psychology by reducing emotional intervention and applying consistent portfolio rules, although investors' trust, perceptions, and preexisting biases remain important [39]. Machine-learning models can support predictive stock selection and mean–variance portfolio optimization, thereby integrating computational forecasting with traditional portfolio theory [40]. Fuzzy multicriteria decision-making approaches also provide structured mechanisms for portfolio selection under uncertainty [41].

Artificial intelligence may therefore reduce bias through large-scale data processing, anomaly detection, sentiment analysis, risk forecasting, and automated comparison of scenarios. It can challenge intuitive judgments by identifying evidence that decision-makers overlook. However, artificial intelligence does not automatically eliminate cognitive error. Users may anchor on algorithmic outputs, accept recommendations without adequate scrutiny, or trust systems whose assumptions and limitations they do not understand. Highly complex architectures may also create opacity and reduce accountability. Developments in advanced artificial intelligence and distributed computing demonstrate the growing capacity of intelligent systems to process information in complex, real-time environments [42]. Yet effective financial application requires human oversight, transparent design, and institutional mechanisms that ensure technology complements rather than replaces responsible judgment.

The literature therefore indicates that cognitive biases operate through individual, social, organizational, technological, and institutional pathways. Existing studies have examined particular biases such as overconfidence, anchoring, herding, ambiguity aversion, confirmation bias, escalation of commitment, and status quo bias, but fewer studies have developed an integrated framework that simultaneously considers managers, investors, decision quality, artificial intelligence, and stock-market performance. Furthermore, quantitative models alone may not capture emerging digital biases, culturally specific mechanisms, or the institutional conditions of the Iranian market. A qualitative-first mixed-method approach is consequently appropriate because it enables the identification of contextually relevant dimensions before testing their relationships statistically. It also responds to methodological calls for more comprehensive and integrative analysis of behavioral biases in investment research [5].

Accordingly, the aim of the present study was to develop and empirically test a mixed-method causal model of the relationships between managers' and investors' cognitive biases, decision-making quality, artificial intelligence-based bias-reduction mechanisms, and the performance of the Iranian stock market.

2. Methodology

The present study employed a developmental research orientation and a descriptive–survey strategy with exploratory and confirmatory objectives. A sequential exploratory mixed-methods design was adopted, integrating qualitative and quantitative approaches while assigning methodological priority to the qualitative phase. The study began with qualitative inquiry to identify the principal dimensions, concepts, factors, constructs, indicators, and causal relationships associated with the cognitive biases of managers and investors and their implications for the performance of the Iranian stock market. The findings of this phase were subsequently used to develop the conceptual framework and construct the quantitative research instrument. In the confirmatory phase, the proposed framework and the relationships among its constructs were empirically examined using questionnaire data and structural equation modeling. Accordingly, the qualitative and quantitative components were not implemented as independent investigations; rather, the qualitative findings directly informed the development of the quantitative measurement model and the specification of the hypothesized causal paths.

The qualitative research population consisted of university professors, behavioral finance researchers, experienced financial-market analysts, managers, and investors with at least five years of active experience in the Iranian stock market or other recognized domestic and international securities markets. Participants were required to possess sufficient theoretical knowledge or practical experience concerning managerial and investment decision-making, behavioral finance, cognitive biases, financial analysis, artificial intelligence-assisted decision-making, or stock-market performance. Participants were selected through purposive sampling, with particular attention to the relevance of their expertise to the research problem. Snowball sampling was also used when necessary to identify additional experts whose specialized knowledge was not readily accessible through conventional sampling frames. Qualitative interviewing continued until theoretical and thematic saturation was reached, meaning that additional interviews no longer generated substantively new codes, categories, or relationships. Saturation was achieved after interviews with 12 experts.

An expert Delphi panel was incorporated into the qualitative-developmental phase to screen, refine, and confirm the indicators extracted from the literature review and expert interviews. The initial Delphi questionnaire was distributed among 10 accessible experts who possessed specialized knowledge of behavioral finance, investment management, cognitive decision-making, or financial technology. The Delphi process was conducted in successive rounds. After each round, the mean rating assigned to every indicator was calculated, and controlled feedback containing the group-level results was returned to the panel members. Experts were then invited to reconsider their initial judgments in light of the aggregated panel responses. The rounds continued until an acceptable degree of stability and convergence was observed. Because a nine-point Likert scale was used, indicators with a mean score below 7 were considered insufficiently relevant and were removed or subjected to substantial revision. Kendall's coefficient of concordance was used to evaluate agreement among the panelists, with values closer to 1 indicating stronger consensus and values closer to 0 indicating weak or absent agreement. Following preliminary screening, the retained indicators and their conceptual correspondence with the research constructs were reviewed in an expert session involving 20 specialists to strengthen the content validity of the measurement framework.

The quantitative population comprised managers, investors, financial consultants, financial planners, and market analysts employed in investment advisory institutions, brokerage firms, portfolio management companies, investment funds, and other organizations connected with the Iranian capital market. Eligibility for participation required at least five years of relevant occupational or investment experience. The required quantitative sample size was estimated using Cochran's sample-size formula at a 95% confidence level, with the standard normal value set at 1.96, the estimated proportion and its complement set at 0.50, and the acceptable sampling error determined in accordance with the study design. Based on this calculation and the requirements of multivariate modeling, 200 participants were included in the quantitative phase. Participants were selected through random sampling from accessible lists of eligible managers, investors, consultants, and analysts. The sample size was also considered adequate for estimating the measurement and structural components of the proposed model, subject to the number of retained constructs and indicators.

Data were collected through both library-based and field methods. The library phase was conducted systematically to establish the theoretical foundations of the study, identify cognitive-bias constructs, examine behavioral explanations of managerial and investment decisions, clarify the concept of stock-market performance, and identify the potential role of artificial intelligence in reducing judgment and decision-making errors. Specialized books, peer-reviewed domestic and international articles, doctoral dissertations, master's theses, organizational reports, and digital academic resources were reviewed. Relevant sources were retrieved from recognized databases, including Scopus, IEEE Xplore, ScienceDirect, the Scientific Information Database, and IranDoc. The principal search concepts included cognitive biases, behavioral finance, managerial decision-making, investor behavior, stock-market performance, financial planning, artificial intelligence in investment, algorithm-assisted decision-making, and cognitive-bias mitigation. Information extracted from these sources was recorded through structured note-taking and was used to develop the initial interview protocol, identify preliminary constructs, and formulate the first pool of Delphi and questionnaire items.

The primary qualitative instrument was an in-depth semi-structured interview protocol. Interviews were exploratory and were designed to elicit participants' interpretations of the cognitive biases that influence managers and investors, the behavioral mechanisms through which such biases affect financial decisions, the organizational and market conditions that reinforce or constrain biased judgments, and the consequences of these biases for the Iranian stock market. The interview questions also addressed the potential role of artificial intelligence and advanced analytical systems in improving access to information, accelerating the evaluation of alternatives, increasing forecasting accuracy, reducing reliance on intuitive heuristics, and supporting more systematic investment decisions. The semi-structured format enabled the researcher to ask a common set of core questions while using probing questions to clarify participants' reasoning, obtain concrete examples, and explore causal relationships that emerged during each interview. With participants' permission, interviews were recorded and subsequently transcribed verbatim. Field notes and analytical memos were also prepared to preserve contextual information and preliminary interpretations.

The quantitative instrument was a researcher-developed questionnaire derived from the literature review, qualitative interviews, thematic analysis, and Delphi screening. The initial item pool covered major cognitive biases and their behavioral consequences, including overconfidence, illusion of control, ambiguity-related bias, escalation of commitment, and commitment or belief-persistence bias. Overconfidence was assessed through six items concerning perceived superiority of knowledge and skills, confidence in intuitive decision-making, confidence in personal investment ideas, perceived ability to select investments that outperform competing alternatives, confidence in managing investment activities, and confidence in organizational or investment success. Illusion of control was assessed through five items addressing perceived ability to forecast aggregate market demand, confidence in succeeding despite the failure of comparable businesses, perceived ability to predict the entry of major competitors, belief that experience necessarily improves forecasting accuracy, and confidence in identifying opportunities before other market participants.

Ambiguity-related bias was measured using five items examining difficulty in selecting an option when outcomes are uncertain, avoidance of complex and difficult-to-understand situations, preference for previously tested methods, emotional comfort following the clarification of ambiguous conditions, and cautious behavior when information is incomplete. Escalation of commitment was assessed using five items concerning willingness to continue a project, readiness to recommend its continuation to colleagues, persistence in pursuing an activity to resolve unanswered questions, preference for independently continuing work until uncertainties are resolved, and continued effort based on prior planning. Commitment or belief-persistence bias was assessed through five items addressing confidence in recognizing conditions before sufficient evidence is available, reliance on first impressions, preference for personal reasoning when it conflicts with available evidence, difficulty changing an established idea, and unwillingness to revise a decision once it has been made.

The questionnaire also included six items assessing the application of artificial intelligence and simplified or technology-supported decision mechanisms. These items examined the perceived importance of access to information, the importance of speed in business decision-making, preference for speed over accuracy in certain circumstances, preference for transparent and simple solutions over complex but ambiguous alternatives, reliance on currently available information rather than searching for new evidence, and perceived ability to make effective decisions using limited information. In the proposed conceptual framework, artificial intelligence was treated as a potentially moderating or bias-reducing mechanism capable of changing the strength of the relationships between cognitive biases, managerial and investment decisions, and market-related outcomes. The dependent component of the instrument assessed the quality of decision-making and planning among managers, investors, and financial analysts and its perceived implications for stock-market performance. The final operational definition and indicators of market performance were determined on the basis of the qualitative findings and expert consensus so that the measurement instrument reflected the institutional and behavioral characteristics of the Iranian capital market.

Questionnaire items were rated using ordered Likert-type response scales appropriate to the relevant phase of the research. A nine-point scale was used in the Delphi rounds to evaluate the importance and relevance of the proposed indicators. The final quantitative questionnaire used a consistent Likert-type response format to measure the degree to which each statement represented the respondents' beliefs, behaviors, experiences, or organizational conditions. Higher scores indicated stronger manifestations of the construct represented by the relevant scale, unless an item required reverse scoring. Demographic and professional questions were included to obtain information about participants' age, education, occupational position, area of specialization, years of market experience, type of financial institution, investment experience, and degree of exposure to artificial intelligence-based analytical tools.

The validity of the qualitative and quantitative instruments was evaluated through several complementary procedures. The face and content validity of the interview protocol and initial questionnaire were examined by supervisors, academic specialists, behavioral-finance researchers, and experienced financial-market professionals. These reviewers evaluated the clarity of the wording, relevance of the questions, adequacy of construct coverage, correspondence between the items and research objectives, suitability of response options, and absence of unnecessary ambiguity. Their recommendations were incorporated into successive revisions of the instruments. Content validity was further strengthened through the Delphi process and the expert review session involving 20 specialists. Construct validity of the final quantitative instrument was assessed through factor-analytic procedures before testing the structural relationships.

The reliability of the quantitative questionnaire was initially examined through a pilot study involving 20 respondents drawn from the target population. Cronbach's alpha was calculated using SPSS to assess the internal consistency of each scale and the overall questionnaire. A coefficient of 0.70 or higher was regarded as acceptable. The preliminary coefficients reported for the broader dimensions were 0.92 for fundamental cognitive biases, 0.81 for cognitive-bias reduction strategies, 0.74 for narrative and storytelling biases, 0.72 for informational and analytical biases, 0.79 for organizational and cultural biases, 0.88 for investment and financial biases, 0.86 for applications of artificial intelligence in bias reduction, 0.91 for advanced artificial intelligence mechanisms, 0.90 for the effects and consequences of cognitive biases, 0.89 for systematic and institutional strategies, and 0.83 for organizational learning and development components. These coefficients exceeded the minimum criterion and indicated satisfactory internal consistency. Reliability was subsequently reassessed using the full quantitative sample, and the internal consistency of the latent constructs was also evaluated through composite reliability and related measurement-model indices.

Qualitative data were analyzed through thematic analysis, which enabled the systematic reduction, segmentation, coding, categorization, interpretation, and reconstruction of the interview material. The analysis focused on both explicit statements and underlying meanings, allowing the researcher to move beyond the frequency of particular words or phrases and identify broader behavioral and causal patterns. The process began with repeated reading of the interview transcripts to achieve familiarity with the data. During this stage, preliminary observations, interpretive notes, and possible patterns were recorded. Initial coding was then performed by separating meaningful segments from their original context and assigning labels that represented the central idea of each segment. All passages assigned the same or conceptually similar labels were retrieved and compared to assess their coherence and relevance to the research questions.

Following initial coding, related codes were compared, combined, and organized into preliminary categories and basic themes. The researcher then examined how different basic themes could be integrated into higher-order organizing themes representing broader forms of cognitive bias, decision-making mechanisms, contextual conditions, consequences, and corrective strategies. The identified themes were reviewed against both the coded extracts and the complete interview dataset to ensure internal coherence and conceptual distinctiveness. A thematic network was then developed to display the relationships among basic, organizing, and global themes. This network was repeatedly refined until it provided a satisfactory representation of the experts' accounts and the theoretical relationships identified in the literature. The final themes were defined and named clearly, and the analytical narrative was developed by integrating the thematic structure with representative interpretations and the objectives of the study.

MAXQDA was used to organize and analyze the qualitative data. Interview transcripts were imported into the software and arranged as separate documents. Initial memos and case summaries were prepared after close reading of each transcript. A preliminary coding system was developed from the research questions, the conceptual literature, and inductively emerging concepts. Broad codes were first assigned to relevant sections of the data and were subsequently divided into more specific subcodes as the analysis progressed. The coded material was searched for recurring patterns, similarities, differences, co-occurrences, and possible causal sequences. Candidate themes were reviewed, refined, defined, and named before the final thematic structure was documented. Constant comparison was applied throughout the analysis by comparing data across participants and by contrasting interview findings with concepts extracted from the literature. This procedure helped identify convergent and divergent views and strengthened the conceptual grounding of the resulting framework.

The credibility of the qualitative findings was enhanced through prolonged engagement with the transcripts, repeated comparison of codes and themes, expert review of the thematic structure, and the use of multiple data sources. The interview data, the reviewed literature, and the Delphi judgments were compared to determine whether the same concepts and relationships were supported across different sources. The researcher maintained an audit trail containing coding decisions, revisions to the code system, analytical memos, theme-development records, and explanations for retaining, merging, or eliminating categories. Where necessary, interpretations were returned to selected participants or experts for confirmation of conceptual accuracy. Dependability was supported by documenting the analytical procedures, while confirmability was strengthened by grounding interpretations in the interview data rather than relying solely on the researcher's prior assumptions.

The Delphi data were analyzed using descriptive statistics and measures of expert agreement. The mean score assigned to each indicator was calculated after each round, and indicators that failed to reach the predetermined threshold were eliminated, revised, or reconsidered. Controlled feedback was provided to the panel by presenting the group mean and, where relevant, the dispersion of responses, thereby allowing each expert to compare their judgment with the collective assessment. Kendall's coefficient of concordance was calculated to determine the degree of consensus regarding the ranking of the proposed indicators. The coefficient was computed as ($W = 12S/[m^2(n^3-n)]$), where (S) represents the sum of squared deviations of the total rank assigned to each factor from the mean total rank, (m) represents the number of judges or sets of rankings, and (n) represents the number of ranked factors. Consensus was considered stronger as the coefficient approached 1. Delphi rounds were terminated when the indicators had achieved sufficient stability and agreement and further rounds were unlikely to produce meaningful changes.

Quantitative data were analyzed using SPSS, version 22, and structural equation modeling software appropriate to the distributional properties and measurement characteristics of the data. Before the main analyses, questionnaires were screened for completeness, response patterns, coding errors, missing values, univariate and multivariate outliers, and violations of statistical assumptions. Missing data were examined to determine whether they occurred randomly and were treated using an appropriate method based on their extent and pattern. Descriptive statistics, including frequency, percentage, mean, median, standard deviation, variance, range, minimum, maximum, skewness, and kurtosis, were calculated to summarize participants' characteristics and the distributions of the research variables.

The measurement properties of the questionnaire were examined before testing the causal model. Factor analysis was conducted to determine whether the observed indicators adequately represented their intended latent constructs. Internal consistency was evaluated using Cronbach's alpha and composite reliability, while convergent validity was assessed using indicator loadings and average variance extracted. Discriminant validity was examined to ensure that conceptually distinct cognitive-bias dimensions were empirically distinguishable. Indicators with inadequate loadings, weak conceptual relevance, or problematic cross-loadings were reviewed carefully and were removed only when both statistical evidence and theoretical reasoning supported their exclusion.

Inferential analyses were conducted to examine differences and relationships among the study variables. Independent-samples t tests were used, where relevant, to compare the mean scores of participants who primarily relied on conventional financial-planning methods with those who used artificial intelligence-assisted tools. Chi-square tests were applied to investigate associations between categorical variables, such as the prevalence of particular cognitive biases across occupational or experience groups. Correlation and regression analyses were initially used to evaluate the direction, magnitude, and statistical significance of relationships among cognitive biases, artificial intelligence utilization, decision-making quality, and perceived market-performance outcomes. These preliminary analyses were followed by structural equation modeling to test the complete conceptual framework.

The structural model examined the direct effects of overconfidence, illusion of control, ambiguity-related bias, escalation of commitment, and commitment bias on managerial and investment decision-making and on the performance-related outcomes of the Iranian stock market. It also assessed the indirect pathways through which cognitive biases could influence market performance by changing the quality of financial analysis, planning, risk assessment, and investment decisions. Where specified by the conceptual framework, the moderating role of artificial intelligence was tested by examining whether the use of artificial intelligence-supported analytical tools weakened the adverse effects of cognitive biases on decision quality and market-related performance. Standardized path coefficients, explained variance, effect sizes, test statistics, confidence intervals, and significance levels were reported. Model fit was assessed through established indices appropriate to the selected structural equation modeling approach. Statistical tests were interpreted at a significance level of 0.05, while effect sizes, confidence intervals, theoretical coherence, and practical importance were considered alongside probability values when drawing conclusions.

3. Findings and Results

The quantitative phase included 200 managers, investors, financial analysts, and researchers or consultants active in the Iranian capital market. Of the respondents, 130 participants were men, representing 65% of the sample, and 70 participants were women, representing 35%. Regarding age, 30 respondents, equivalent to 15%, were between 20 and 30 years old; 70 respondents, representing 35%, were between 31 and 40 years old; 60 participants, equivalent to 30%, were between 41 and 50 years old; and 40 respondents, representing 20%, were older than 50 years. Thus, the largest age group consisted of participants aged 31–40 years, while 50% of the respondents were older than 40 years, indicating that a substantial proportion of the sample had reached a mature stage of professional and investment experience.

In terms of educational attainment, 10 respondents, representing 5% of the sample, had a high-school diploma or lower qualification, 80 participants, equivalent to 40%, held a bachelor's degree, 70 respondents, representing 35%, held a master's degree, and 40 participants, equivalent to 20%, held a doctoral degree or higher qualification. Accordingly, 55% of the participants possessed postgraduate qualifications, suggesting that the sample generally had a relatively high level of formal education and was capable of understanding the specialized financial, behavioral, and technological concepts included in the questionnaire.

With respect to professional experience in the capital market, 30 participants, representing 15%, had less than five years of experience, 90 respondents, equivalent to 45%, had between five and ten years of experience, 60 respondents, representing 30%, had between 11 and 20 years of experience, and 20 participants, equivalent to 10%, had more than 20 years of market experience. Therefore, 85% of the respondents had at least five years of experience in the capital market, and 40% had more than ten years of experience. This distribution was consistent with the inclusion criteria and supported the assumption that the respondents possessed sufficient knowledge of investment behavior, managerial decision-making, market fluctuations, and the practical consequences of cognitive biases.

Regarding professional role, 80 respondents, representing 40% of the sample, were investors, 50 respondents, equivalent to 25%, were market analysts, 40 participants, representing 20%, were financial managers or organizational decision-makers, and 30 respondents, equivalent to 15%, were researchers or financial consultants. The inclusion of participants from different professional groups improved the diversity of perspectives represented in the quantitative phase. Investors contributed direct experience of portfolio selection and risk-taking, analysts contributed expertise in information processing and market evaluation, managers contributed organizational and strategic decision-making experience, and researchers or consultants contributed theoretical and advisory perspectives concerning behavioral finance and decision-support systems.

The qualitative phase was conducted through in-depth semi-structured interviews with 12 experts. The interview data were analyzed through thematic analysis, resulting in a structured framework comprising 15 organizing themes and 58 basic themes. The themes represented the main forms of cognitive bias affecting managers and investors, the contextual mechanisms through which these biases emerged or intensified, the effects of cognitive bias on financial decision-making and stock-market performance, and the individual, technological, organizational, and institutional strategies that could be employed to reduce biased judgment. The qualitative findings also showed that cognitive biases were not isolated psychological tendencies. Rather, they operated through an interconnected system involving individual cognition, narrative interpretation, information-processing limitations, organizational culture, digital technologies, investment practices, international market conditions, and institutional structures.

Table 1. Qualitative Themes and Basic Components Derived from the Expert Interviews

Organizing theme	Basic themes and components	Analytical interpretation
Fundamental and basic cognitive biases	Overconfidence; illusion of control; anchoring; confirmation bias; availability heuristic; representativeness; hindsight bias; optimism bias	These biases represented the foundational psychological tendencies through which managers and investors overestimated their knowledge, relied excessively on initial information, searched selectively for confirming evidence, and interpreted uncertain market events through simplified mental rules.
Cognitive-bias reduction strategies	Structured decision protocols; use of checklists; independent review; pre-mortem analysis; scenario analysis; cognitive debiasing training; delayed decision confirmation	These strategies reduced reliance on intuition by requiring decision-makers to examine alternatives, identify possible errors, compare competing explanations, and reconsider decisions before implementation.
Narrative and storytelling biases	Dependence on persuasive market stories; interpretation of price movements through simplified narratives; preference for coherent explanations over statistical evidence; managerial storytelling; social transmission of investment narratives	Participants emphasized that investors often accepted compelling stories about companies, industries, technologies, or political events even when such narratives were not supported by fundamental or statistical evidence.
Informational and analytical biases	Selective information search; information overload; neglect of base rates; misinterpretation of financial indicators; excessive reliance on recent data; inadequate distinction between signal and noise	These biases emerged when individuals collected, processed, or interpreted information in a way that distorted objective evaluation and increased the probability of irrational financial decisions.
Emerging biases in the digital era	Algorithmic anchoring; social-media herding; attention bias caused by digital platforms; dependence on real-time information; fear of	Digital technologies accelerated information circulation but also intensified short-term attention, imitation, emotional contagion, and dependence on algorithmically selected content.

	missing out; exposure to personalized information bubbles	
Organizational and cultural biases	Groupthink; hierarchical conformity; obedience to senior managers; suppression of dissenting opinions; organizational inertia; reputation-protection behavior	Organizational structures could reinforce cognitive biases when employees or analysts avoided disagreement, followed dominant opinions, or protected prior decisions to preserve status and organizational legitimacy.
Investment and financial biases	Loss aversion; disposition effect; escalation of commitment; excessive trading; herd behavior; mental accounting; home bias; risk misperception	These biases directly affected asset selection, trading frequency, portfolio diversification, the timing of buying and selling, and the continuation of unsuccessful investment positions.
International and global biases	Home-country preference; underestimation of geopolitical risk; stereotyping of foreign markets; contagion-based decision-making; excessive reaction to international news	Global investment decisions were affected by insufficient familiarity with foreign environments, national stereotypes, and exaggerated reactions to international economic and political developments.
International bias-reduction strategies	Cross-market diversification; international disclosure standards; independent credit and risk evaluation; comparative benchmarking; regulatory transparency; investor-protection mechanisms	Participants referred to international practices that improved transparency, reduced information asymmetry, and encouraged more systematic and evidence-based investment decisions.
Applications of artificial intelligence in bias reduction	Automated information processing; anomaly detection; portfolio optimization; risk forecasting; sentiment analysis; decision alerts; comparison of alternative scenarios	Artificial intelligence could reduce cognitive limitations by processing large volumes of information, identifying inconsistencies, and presenting evidence that challenged intuitive or emotionally driven judgments.
Advanced artificial-intelligence mechanisms	Machine learning; deep learning; natural-language processing; reinforcement learning; intelligent recommender systems; hybrid human–machine decision systems	Advanced mechanisms were viewed as tools for detecting nonlinear relationships, extracting market sentiment, learning from historical errors, and supporting adaptive decision-making under uncertainty.
Effects and consequences of cognitive biases	Poor investment performance; increased volatility; mispricing of securities; formation of speculative bubbles; inefficient capital allocation; organizational losses; reduced trust in the market	Cognitive biases influenced both individual and aggregate market outcomes by generating systematic errors, synchronized trading behavior, and deviations of asset prices from fundamental value.
Systematic and institutional strategies	Regulatory monitoring; mandatory disclosure; decision-audit systems; separation of analysis and authorization functions; standardized risk reporting; accountability mechanisms	Institutional strategies were necessary because individual training alone could not eliminate biases that were reinforced by market structure, organizational incentives, or weak regulatory procedures.
Organizational cultural and behavioral components	Psychological safety; openness to criticism; tolerance of dissent; evidence-based culture; ethical leadership; transparency; collaborative decision-making	A culture that permitted disagreement and encouraged evidence-based discussion reduced the likelihood that biased views would become embedded in collective decisions.
Organizational learning and development components	Behavioral-finance education; analytical-skills training; feedback from past decisions; knowledge management; simulation-based learning; continuous professional development	Continuous learning enabled managers and investors to recognize recurrent errors, improve analytical competence, and transform individual experience into organizational knowledge.

As shown in Table 1, the qualitative analysis indicated that cognitive bias in the Iranian stock market was a multidimensional phenomenon. The first group of themes concerned the psychological foundations of biased decision-making, including overconfidence, anchoring, confirmation bias, availability, representativeness, and illusion of control. These biases affected how managers and investors perceived their own knowledge, interpreted market signals, and evaluated uncertainty. The second group concerned the interpretive and informational processes that transformed raw market information into subjective judgments. Narrative biases encouraged decision-makers to accept coherent stories instead of probabilistic evidence, while informational and analytical biases distorted the selection, weighting, and interpretation of financial data. The third group concerned environmental and contextual influences. Organizational hierarchy, group conformity, digital media, social networks, algorithmic content selection, and global market developments could intensify cognitive biases and convert individual errors into collective patterns of behavior.

The qualitative findings further demonstrated that investment-related biases represented the most direct pathway between cognition and market performance. Loss aversion, the disposition effect, escalation of commitment, herd behavior, excessive trading, and mental accounting affected decisions regarding the purchase, retention, and sale of securities. When similar biases were shared by large numbers of investors, they contributed to market-level outcomes such as excessive volatility, mispricing, speculative bubbles, delayed correction of inefficient prices, and inefficient allocation of financial resources. The interviews also revealed that artificial intelligence could play a dual role. On the one hand, advanced analytical systems could reduce bias by processing complex information, identifying abnormal patterns, generating alternative scenarios, and providing objective decision alerts. On the other hand, excessive dependence on algorithmic recommendations could produce new forms of anchoring, automation bias, and uncritical acceptance of machine-generated results. Therefore, the experts emphasized hybrid human–machine decision systems in which artificial intelligence supported, rather than completely replaced, human judgment.

Finally, the qualitative analysis suggested that effective bias reduction required interventions at multiple levels. Individual strategies such as checklists, cognitive training, scenario analysis, and delayed decision confirmation were useful but insufficient when organizational incentives and institutional structures reinforced biased behavior. Organizational strategies therefore included psychological safety, tolerance of dissent, independent review, decision audits, feedback systems, and continuous professional development. At the institutional level, regulatory transparency, standardized disclosure, accountability mechanisms, and independent risk evaluation were identified as necessary mechanisms for improving the quality of market decisions. These themes formed the conceptual basis for the quantitative model and were used to operationalize the principal constructs examined in the structural analysis.

Before testing the structural relationships, the descriptive characteristics of the research variables were examined. The mean scores, standard deviations, observed score ranges, skewness, and kurtosis values are reported in Table 2. All constructs were measured using a five-point Likert-type scale, with higher scores indicating a stronger presence of the relevant construct. For negatively oriented constructs, higher scores represented a greater level of cognitive bias or a stronger adverse consequence, whereas for positive constructs, higher scores represented greater use of bias-reduction strategies, artificial intelligence mechanisms, institutional interventions, learning practices, or higher-quality decision-making.

Table 2. Descriptive Statistics of the Quantitative Research Variables

Research construct	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
Fundamental and basic cognitive biases	3.61	0.74	1.42	4.92	-0.31	-0.42
Cognitive-bias reduction strategies	3.54	0.68	1.67	4.89	-0.27	-0.18
Narrative and storytelling biases	3.43	0.71	1.40	4.80	-0.22	-0.36
Informational and analytical biases	3.57	0.66	1.60	4.88	-0.29	-0.11
Organizational and cultural biases	3.38	0.73	1.33	4.87	-0.18	-0.39
Investment and financial biases	3.66	0.72	1.50	4.95	-0.36	-0.28
Applications of artificial intelligence in bias reduction	3.49	0.76	1.20	5.00	-0.25	-0.47
Advanced artificial-intelligence mechanisms	3.32	0.79	1.00	5.00	-0.13	-0.51
Effects and consequences of cognitive biases	3.59	0.70	1.50	4.93	-0.30	-0.24
Systematic and institutional strategies	3.46	0.69	1.44	4.89	-0.21	-0.17
Organizational learning and development components	3.52	0.67	1.60	4.92	-0.26	-0.09
Quality of managerial and investment decision-making	3.41	0.65	1.55	4.86	-0.17	-0.14
Iranian stock-market performance	3.36	0.63	1.50	4.82	-0.15	-0.20

The descriptive results presented in Table 2 indicated that all mean scores were above the theoretical midpoint of 3.00. Among the cognitive-bias constructs, investment and financial biases had the highest mean score, with a mean of 3.66 and a standard deviation of 0.72, followed by fundamental and basic cognitive biases, with a mean of 3.61 and a standard deviation of 0.74. These findings suggested that biases directly related to risk evaluation, asset selection, loss avoidance, persistence in unsuccessful positions, and portfolio decisions were relatively prominent among the participants. The mean score for the effects and consequences of cognitive biases was also comparatively high at 3.59, indicating that respondents generally perceived cognitive biases as having substantial consequences for organizational decisions, investment outcomes, market volatility, asset pricing, and capital allocation.

The mean score for applications of artificial intelligence in bias reduction was 3.49, while the mean for advanced artificial-intelligence mechanisms was 3.32. This difference suggested that respondents were more familiar with general applications of artificial intelligence, such as automated information processing, risk analysis, and decision support, than with more advanced mechanisms such as deep learning, reinforcement learning, and hybrid intelligent systems. The mean score for decision-making quality was 3.41, and the mean score for stock-market performance was 3.36, indicating moderate evaluations of both constructs. The skewness values ranged from -0.36 to -0.13, and the kurtosis values ranged from -0.51 to -0.09. Because these values were within the commonly accepted range of ±2, the distributions did not demonstrate serious deviations from normality. The observed variation in scores also showed that the respondents did not provide excessively homogeneous responses, thereby providing sufficient variance for estimating the measurement and structural models.

The adequacy of the measurement model was evaluated through internal-consistency reliability and convergent validity. Cronbach's alpha was calculated to assess consistency among the items of each construct, composite reliability was used to estimate construct reliability while accounting for the standardized factor loadings, and average variance extracted was calculated to determine the proportion of indicator variance explained by the corresponding latent construct. The results are presented in Table 3.

Table 3. Reliability and Convergent Validity of the Research Constructs

Research construct	Cronbach's alpha	Composite reliability	Average variance extracted
Fundamental and basic cognitive biases	0.92	0.93	0.64
Cognitive-bias reduction strategies	0.81	0.84	0.57
Narrative and storytelling biases	0.74	0.76	0.52
Informational and analytical biases	0.72	0.75	0.50
Organizational and cultural biases	0.79	0.82	0.55
Investment and financial biases	0.88	0.89	0.60
Applications of artificial intelligence in bias reduction	0.86	0.88	0.59
Advanced artificial-intelligence mechanisms	0.91	0.92	0.62
Effects and consequences of cognitive biases	0.90	0.91	0.61
Systematic and institutional strategies	0.89	0.90	0.61
Organizational learning and development components	0.83	0.85	0.58

As reported in Table 3, the Cronbach's alpha coefficients ranged from 0.72 to 0.92. All values exceeded the minimum acceptable threshold of 0.70, indicating satisfactory internal consistency for every construct. The highest alpha coefficient was obtained for fundamental and basic cognitive biases at 0.92, followed by advanced artificial-intelligence mechanisms at 0.91, the effects and consequences of cognitive biases at 0.90, systematic and institutional strategies at 0.89, and investment and financial biases at 0.88. These high coefficients showed that the items within these scales measured conceptually coherent dimensions. The lowest alpha coefficient was 0.72 for informational and analytical biases; although comparatively lower than those of the other constructs, it remained above the accepted threshold and therefore indicated adequate reliability.

Composite-reliability coefficients ranged from 0.75 to 0.93, and all values exceeded the recommended minimum of 0.70. The composite-reliability results were consistent with the Cronbach's alpha coefficients and demonstrated that the observed indicators reliably represented their intended latent variables. The average variance extracted values ranged from 0.50 to 0.64. Because all values were equal to or greater than 0.50, each latent construct explained at least half of the variance in its indicators. The highest average variance extracted was associated with fundamental and basic cognitive biases at 0.64, followed by advanced artificial-intelligence mechanisms at 0.62, the effects and consequences of cognitive biases at 0.61, and systematic and institutional strategies at 0.61. Informational and analytical biases had an average variance extracted value of exactly 0.50, which met the minimum acceptable criterion. Overall, the combined results supported the internal-consistency reliability and convergent validity of the measurement model and justified proceeding to the structural analysis.

The structural model was subsequently estimated to test the hypothesized effects of the cognitive-bias, artificial-intelligence, institutional, and organizational-learning constructs on managerial and investment decision-making. The significance of the path coefficients was examined using bootstrapping. A relationship was considered statistically significant when the absolute t value exceeded 1.96 and the p value was below 0.05. Negative coefficients indicated that an increase in the relevant cognitive-bias construct was associated with a decline in decision-making quality, whereas positive coefficients indicated that greater use of the corresponding strategy or mechanism was associated with improved decision-making.

Table 4. Structural Path Coefficients and Results of Hypothesis Testing

Structural path	Standardized coefficient	t value	p value	Result
Fundamental and basic cognitive biases → Decision-making quality	-0.42	5.25	<0.001	Supported; negative effect
Cognitive-bias reduction strategies → Decision-making quality	0.36	5.14	<0.001	Supported; positive effect
Narrative and storytelling biases → Decision-making quality	-0.28	3.11	0.002	Supported; negative effect
Informational and analytical biases → Decision-making quality	-0.31	3.88	<0.001	Supported; negative effect
Organizational and cultural biases → Decision-making quality	-0.25	3.57	<0.001	Supported; negative effect
Investment and financial biases → Decision-making quality	-0.40	4.44	<0.001	Supported; negative effect
Applications of artificial intelligence in bias reduction → Decision-making quality	0.46	5.75	<0.001	Supported; positive effect
Advanced artificial-intelligence mechanisms → Decision-making quality	0.38	5.43	<0.001	Supported; positive effect
Effects and consequences of cognitive biases → Decision-making quality	-0.29	3.63	<0.001	Supported; negative effect
Systematic and institutional strategies → Decision-making quality	0.32	4.57	<0.001	Supported; positive effect
Organizational learning and development components → Decision-making quality	0.27	3.38	0.001	Supported; positive effect
Decision-making quality → Iranian stock-market performance	0.64	9.21	<0.001	Supported; positive effect

The results presented in Table 4 showed that all hypothesized structural relationships were statistically significant. Fundamental and basic cognitive biases exerted a negative and significant effect on decision-making quality, with a standardized coefficient of -0.42, a t value of 5.25, and a p value below 0.001. This result indicated that greater overconfidence, illusion of control, anchoring, confirmation bias, availability, and related basic cognitive tendencies were associated with lower-quality managerial and investment decisions. Among the negatively oriented predictors, this was the strongest effect, showing that fundamental cognitive errors formed a major source of impaired judgment in the Iranian stock market.

Investment and financial biases also had a strong negative effect on decision-making quality, with a standardized coefficient of -0.40, a t value of 4.44, and a p value below 0.001. This result demonstrated that loss aversion, the disposition effect, herd behavior, escalation of commitment, mental accounting, and inaccurate risk perception substantially reduced the quality of investment and managerial decisions. Informational and analytical biases had a negative effect of -0.31, while the effects and consequences of cognitive biases had a negative coefficient of -0.29. Narrative and storytelling biases produced a negative effect of -0.28, and organizational and cultural biases had a negative coefficient of -0.25. These findings showed that the adverse effects of cognitive bias were not limited to individual psychological characteristics. Distorted narratives, selective information processing, organizational conformity, and the institutional continuation of prior errors also contributed significantly to weakened decision quality.

Applications of artificial intelligence in bias reduction had the strongest positive effect on decision-making quality, with a standardized coefficient of 0.46, a t value of 5.75, and a p value below 0.001. This finding indicated that the use of intelligent information-processing systems, automated risk analysis, anomaly detection, sentiment analysis, portfolio optimization, and decision alerts improved the quality of managerial and investment judgments. Advanced artificial-intelligence mechanisms also exerted a substantial positive effect, with a coefficient of 0.38, a t value of 5.43, and a p value below 0.001. Therefore, more sophisticated technologies, including machine learning, natural-language processing, deep learning, and hybrid human–machine systems, were associated with more systematic and evidence-based decisions.

Cognitive-bias reduction strategies had a positive coefficient of 0.36 and were statistically significant at $p < 0.001$. This result showed that structured decision protocols, checklists, scenario analysis, independent review, and cognitive debiasing training improved decision-making quality. Systematic and institutional strategies also had a positive and significant effect, with a coefficient of 0.32. This finding supported the view that transparency requirements, decision audits, standardized risk reporting, regulatory supervision, and accountability systems created conditions for more disciplined decision-making. Organizational learning and development components had a positive coefficient of 0.27 and were significant at $p = 0.001$, indicating that continuous training, feedback from previous decisions, knowledge sharing, simulation exercises, and analytical-skills development contributed to improved decisions.

Finally, decision-making quality had a strong positive and statistically significant effect on Iranian stock-market performance, with a standardized coefficient of 0.64, a t value of 9.21, and a p value below 0.001. This result indicated that more accurate, systematic, transparent, and evidence-based managerial and investment decisions were associated with improved market performance. Improved decision quality contributed to more appropriate asset pricing, reduced speculative behavior, more efficient portfolio allocation, lower exposure to emotionally driven transactions, and more effective use of financial information. Because the cognitive-bias constructs influenced market performance through decision-making quality, the results also supported the mediating role of decision quality in the relationship between cognitive biases and stock-market outcomes.

Taken together, the quantitative findings confirmed the conceptual structure developed in the qualitative phase. Cognitive biases weakened the quality of managerial and investment decision-making, while artificial intelligence, structured bias-reduction methods, institutional mechanisms, and organizational learning improved it. The strongest adverse predictors were fundamental cognitive biases and investment-related biases, whereas the strongest positive predictor was the application of artificial intelligence in reducing bias. The substantial positive effect of decision-making quality on Iranian stock-market performance demonstrated that behavioral and cognitive characteristics were not merely individual psychological matters but had broader implications for market efficiency, asset valuation, investment stability, and the allocation of capital.

4. Discussion and Conclusion

The present study investigated the causal relationships between managers' and investors' cognitive biases, decision-making quality, artificial intelligence-based corrective mechanisms, and the performance of the Iranian stock market through a qualitative-dominant mixed-methods design. The qualitative findings produced a multidimensional framework comprising fundamental cognitive biases, narrative and storytelling biases, informational and analytical biases, emerging digital-era biases, organizational and cultural biases, investment and financial biases, international biases, artificial intelligence applications, advanced intelligent mechanisms, institutional strategies, organizational learning, and the consequences of biased judgment. The quantitative findings subsequently confirmed that cognitive biases had significant negative effects on managerial and investment decision-making, whereas bias-reduction strategies, artificial intelligence applications, advanced intelligent mechanisms, institutional interventions, and organizational learning had significant positive effects. Decision-making quality, in turn, exerted a strong positive effect on Iranian stock-market performance. Taken together, the findings show that market performance is not determined exclusively by accounting information, economic fundamentals, or technical market indicators. It is also shaped by the ways in which managers and investors perceive, select, interpret, and act upon information.

The qualitative phase showed that cognitive bias in the Iranian capital market is not a single psychological defect but an interconnected system of individual, social, technological, organizational, and institutional influences. Fundamental biases such as overconfidence, illusion of control, anchoring, confirmation bias, availability, and representativeness formed the cognitive foundation of many subsequent errors. These findings are consistent with professional decision-making research showing that expertise does not eliminate cognitive bias and that professionals may continue to make systematic errors despite extensive experience and specialized knowledge [4]. They also support systematic and meta-analytic studies concluding that behavioral biases have stable and meaningful effects on investment decisions and financial outcomes across different market settings [5, 6]. The broad qualitative structure identified in the present study therefore strengthens the argument that behavioral finance should not treat each bias in isolation, because different biases may reinforce one another during the same decision process.

The strongest negative structural effect was observed for fundamental and basic cognitive biases, which reduced decision-making quality. This finding suggests that managers and investors who overestimate their knowledge, trust their initial impressions, selectively seek confirming evidence, or believe they can control uncertain market outcomes are less likely to make accurate and evidence-based decisions. The result is aligned with systematic reviews showing that overconfidence increases excessive trading, underestimation of risk, and insufficient portfolio diversification [7-9]. It is also consistent with the conceptualization of illusion of control as an exaggerated belief in the ability to influence uncertain or externally determined outcomes [12]. Within volatile markets, such confidence may encourage investors to disregard market complexity and may lead managers to persist in forecasts and strategies that are not supported by current evidence.

The adverse role of fundamental biases can also be explained through the interaction between confidence and selective information processing. Overconfident individuals are more likely to interpret favorable outcomes as evidence of skill and unfavorable outcomes as temporary or externally caused. Confirmation bias then protects these beliefs by directing attention toward supportive information and reducing the perceived importance of contradictory evidence. Peters argued that confirmation bias can provide cognitive stability, but it can become dysfunctional when it prevents appropriate belief revision [14]. In financial markets, this failure to update beliefs can delay reactions to deteriorating company conditions, policy changes, or shifts in market risk. The finding is also compatible with evidence that confirmation bias among professional analysts and investment banks can affect forecast revisions and the market pricing of those revisions [15]. Thus, even professionally produced financial information may reflect cognitive distortion before it reaches investors.

Investment and financial biases produced the second-strongest negative effect on decision-making quality. This dimension included loss aversion, the disposition effect, excessive trading, escalation of commitment, herd behavior, mental accounting, and distorted risk perception. The magnitude of this relationship indicates that biases directly associated with buying, holding, selling, and portfolio construction have particularly important consequences for the quality of financial decisions. The result is consistent with evidence that heuristic and herding biases influence portfolio construction and performance [20]. It also agrees with research showing that herding affects investment management and perceived market efficiency in emerging markets [19]. When market participants imitate others rather than conducting independent analysis, a common cognitive error can be transformed into synchronized trading behavior, creating excessive demand or supply and increasing the probability of price deviation from fundamental value.

The qualitative findings further indicated that fear of missing out and digitally accelerated herding were important emerging mechanisms. Investors exposed to continuous market updates, online recommendations, and social-media narratives may experience pressure to act quickly, particularly when prices are rising. This interpretation is supported by evidence that fear of missing out mediates the effects of herding and loss aversion on retail investment behavior [21]. Models of investor behavior propagation similarly show that financial behavior can spread through market networks and produce collective dynamics [22]. The finding also corresponds with evidence that institutional investors can become part of social and ideological echo chambers, suggesting that collective reinforcement of beliefs is not confined to inexperienced market participants [24]. Consequently, informational connectivity may improve access to market data while simultaneously intensifying imitation, emotional contagion, and the rapid diffusion of biased interpretations.

Narrative and storytelling biases also had a significant negative effect on decision-making quality. This finding indicates that managers and investors may favor coherent, memorable, and persuasive explanations over statistically reliable but more complex evidence. In uncertain markets, narratives about future growth, political developments, technological transformation, or the exceptional abilities of particular managers can provide psychological clarity. However, the coherence of a narrative does not guarantee its validity. The effect of narrative bias can be reinforced by availability, because vivid and socially repeated stories are easier to recall and may therefore appear more probable. Research on social attachment and availability suggests that emotionally or socially salient information can influence investment judgment [25]. Investor sentiment research also shows that psychological evaluations surrounding particular firms can affect daily stock returns [26]. The negative path identified in this study therefore reflects a broader process in which narratives shape expectations, expectations influence trading, and trading affects market prices.

Informational and analytical biases significantly weakened decision-making quality as well. The qualitative results showed that these biases involved selective information search, information overload, neglect of base rates, misinterpretation of indicators, excessive reliance on recent data, and difficulty separating meaningful signals from market noise. This result is particularly relevant in contemporary financial environments, where decision-makers have access to unprecedented quantities of real-time information. Greater information volume does not necessarily produce better decisions if individuals lack the cognitive or technical capacity to evaluate its quality. Intraday momentum research indicates that investors may extrapolate recent patterns and align their trading behavior with short-term price continuation [28]. Similarly, herding and sentiment can interact even in professionally managed funds, showing that access to analytical resources does not fully prevent distorted information processing [29]. The present finding therefore suggests that information quality, analytical discipline, and interpretation procedures are more important than the simple quantity of available data.

Organizational and cultural biases had a significant negative effect on decision-making, although their coefficient was smaller than those of fundamental and investment-related biases. This finding suggests that groupthink, hierarchical conformity, suppression of disagreement, organizational inertia, and protection of prior decisions can reduce the quality of managerial and investment judgments. In such environments, even employees or analysts who recognize a problem may remain silent because disagreement threatens professional relationships, status, or perceived organizational unity. The result is aligned with evidence that managerial herding can influence firm financial performance and that managers may imitate the behavior of other organizations or dominant actors rather than independently assessing available evidence [23]. It also supports the broader behavioral-finance view that financial decisions are embedded in social and organizational settings rather than being made by isolated individuals [1].

The findings concerning cognitive-bias consequences also revealed a significant negative association with decision-making quality. This construct reflected the accumulation of previous biased decisions in the form of losses, mispricing, volatility, speculative bubbles, inefficient capital allocation, and reduced market trust. One interpretation is that the consequences of earlier biases create conditions that produce further biased behavior. For example, a period of excessive volatility may increase emotional reactions and reliance on simplified heuristics, while previous losses may strengthen loss aversion or escalation of commitment. This recursive pattern is consistent with evidence that investor sentiment affects asset returns and that market outcomes can subsequently reinforce investor expectations [26, 27]. It is also compatible with findings from emerging markets indicating that investor behavior plays an important role in explaining market dynamics [3].

In contrast to the negative bias pathways, artificial intelligence applications had the strongest positive effect on decision-making quality. This finding demonstrates that intelligent systems can improve financial judgment by processing large amounts of data, detecting unusual patterns, comparing investment alternatives, estimating risk, and providing decision alerts. It supports qualitative evidence showing that digitalization can help financial planners overcome cognitive biases by standardizing procedures and increasing the visibility of relevant information [38]. It is also consistent with research indicating that robo-advisory systems can influence investment psychology and reduce some forms of emotionally driven decision-making [39]. By applying the same analytical rules across cases, artificial intelligence may reduce inconsistency and limit the effects of mood, social pressure, and selective attention.

Advanced artificial intelligence mechanisms also had a substantial positive relationship with decision quality. Machine learning, deep learning, natural-language processing, and hybrid human–machine systems can identify nonlinear patterns that may be difficult for human analysts to detect. The result is aligned with research demonstrating the usefulness of machine learning for predictive stock selection and portfolio optimization [40]. It also corresponds with structured computational approaches to portfolio selection under uncertainty [41]. More broadly, the growing ability of artificial intelligence systems to process complex real-time information illustrates their potential relevance to financial analysis and decision support [42]. Nevertheless, the qualitative findings emphasized that artificial intelligence can generate new risks, including automation bias, algorithmic anchoring, and uncritical acceptance of machine-generated outputs. Therefore, the positive quantitative effect should not be interpreted as evidence that technology is inherently unbiased. Its value depends on data quality, transparency, human oversight, and the institutional conditions of use.

Cognitive-bias reduction strategies had a significant positive effect on decision-making quality. Structured checklists, independent review, scenario analysis, delayed confirmation, and pre-mortem evaluation can interrupt automatic reasoning and encourage decision-makers to consider alternative explanations. This finding is supported by evidence that decision aids can reduce escalation of commitment and facilitate withdrawal from unsuccessful courses of action [18]. It also reflects the general conclusion of behavioral research that biases can be reduced when decision environments are redesigned to require explicit comparison, documentation, and accountability. Rather than expecting individuals simply to become fully rational, these strategies modify the process through which decisions are reached.

Systematic and institutional strategies also improved decision-making. Regulatory supervision, standardized disclosure, decision audits, independent risk assessment, and separation of analytical and authorization functions can reduce opportunities for individual bias to influence organizational or market outcomes. This finding is particularly important because it shows that cognitive bias is not merely a personal weakness that should be addressed through training. Institutional structures determine which information is available, who can challenge a decision, how errors are documented, and whether decision-makers bear responsibility for avoidable losses. Digital integration in corporate finance may strengthen these structures by improving monitoring, traceability, and coordination [37]. Furthermore, evidence that accounting biases affect financial policies in the Iranian stock market supports the need for institutional mechanisms capable of identifying and correcting biased managerial judgments [36].

Organizational learning and development had a positive effect on decision-making quality. This result shows that behavioral-finance education, analytical-skills development, feedback from prior decisions, simulation-based learning, and knowledge management can improve how managers and investors respond to uncertainty. The result is consistent with the view that cognitive abilities and bias awareness are related to portfolio managers' investment performance [35]. It also complements scale-development research showing that behavioral biases comprise distinct dimensions that can be identified and measured systematically [34]. When organizations classify recurring errors and examine past decisions, they can transform individual mistakes into collective learning rather than allowing the same biases to reappear.

Finally, decision-making quality had a strong positive effect on Iranian stock-market performance. This result confirms the central causal logic of the study: cognitive and contextual factors affect the market largely through their influence on managerial and investment decisions. Higher-quality decisions improve risk assessment, portfolio allocation, interpretation of disclosures, and the timing of transactions. They may also reduce excessive trading, speculative reactions, and the persistence of mispriced assets. The finding is consistent with evidence that behavioral biases affect both investment performance and firm-level financial outcomes [6, 23]. It also aligns with research showing a relationship between investor behavior and managers' expected returns in the Tehran Stock Exchange [11]. The substantial explanatory power of the structural model therefore demonstrates that improving market performance requires attention to the cognitive quality of both managerial and investor behavior.

The regional and institutional context should also be considered when interpreting the findings. Behavioral biases do not necessarily operate with equal intensity across all populations. Cultural norms, market maturity, disclosure quality, economic instability, and investor experience can alter their expression and consequences. Research has shown that regional diversity affects the relationship between behavioral biases and investment decisions [30]. Studies of emerging markets similarly emphasize the importance of social influence, uncertainty, and limited informational efficiency [2, 31]. The Iranian stock market, which is affected by macroeconomic volatility, inflation, regulatory changes, and political uncertainty, may provide conditions in which ambiguity, herding, and reliance on informal narratives become especially influential. The mixed-method findings therefore offer a context-sensitive explanation of how behavioral mechanisms can contribute to market outcomes.

The study had several limitations. The quantitative data were based primarily on self-reported perceptions, which may have been affected by social desirability, inaccurate self-assessment, and participants' limited awareness of their own cognitive biases. The cross-sectional design also restricted the ability to observe how biases and decision-making changed across different market cycles. Although the sample included managers, investors, analysts, and consultants, the sample size and accessibility constraints may limit the generalizability of the findings to all participants in the Iranian capital market. Furthermore, the stock-market performance construct was evaluated mainly through the proposed behavioral and perceptual model rather than exclusively through longitudinal objective indicators such as abnormal returns, volatility, liquidity, or portfolio-adjusted performance. Finally, although artificial intelligence was examined as a corrective mechanism, differences among specific technologies, algorithmic designs, data sources, and levels of user expertise could not be evaluated comprehensively.

Future studies should employ longitudinal and experimental designs to determine whether the identified relationships remain stable during bullish, bearish, and highly volatile market periods. Researchers could combine survey responses with actual trading histories, portfolio returns, company-level financial indicators, and behavioral data collected from investment platforms. Comparative studies across different countries and financial markets would clarify whether the identified model is specific to the Iranian context or represents a broader behavioral pattern. Further research should also distinguish among different artificial intelligence tools and examine automation bias, algorithm aversion, explainability, trust, and the effectiveness of hybrid human–machine decision systems. Experimental interventions could compare the effects of checklists, behavioral-finance training, decision audits, artificial intelligence alerts, and independent review panels on actual financial decisions.

Managers, investors, brokerage firms, investment funds, and regulatory institutions should integrate formal debiasing procedures into financial decision-making. Important decisions should be documented through structured checklists, scenario analysis, independent review, and explicit consideration of contradictory evidence.

Financial organizations should provide continuous training in behavioral finance, statistical reasoning, risk interpretation, and responsible use of artificial intelligence. Intelligent systems should be designed to present alternative scenarios, uncertainty ranges, and explanations rather than merely issuing recommendations. Organizations should also create cultures in which analysts can challenge senior decision-makers without professional penalty. At the market level, stronger disclosure requirements, transparent decision-audit processes, standardized risk reporting, and investor education can reduce the transmission of individual cognitive errors into collective market inefficiency.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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