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Foresight Bias in Decision Accuracy and Prevention Frameworks: A Systematic Literature Review

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Abstract

Decision-making accuracy is often compromised by cognitive biases, particularly foresight bias, which distorts future-oriented judgments and leads to suboptimal outcomes in both human and AI-based systems. This research investigates the role of foresight bias in influencing decision accuracy and examines various prevention frameworks to mitigate bias in decision-making processes through a Systematic Literature Review (SLR) approach. A total of 20 recent peer-reviewed articles were systematically analyzed following PRISMA guidelines to identify patterns related to cognitive bias, predictive decision-making, and bias mitigation strategies. The findings reveal that foresight bias significantly reduces decision accuracy by distorting future-oriented judgments, particularly in complex and uncertain environments, and is further reinforced by cognitive tendencies such as overconfidence and illusion of control, as well as biases embedded in artificial intelligence (AI) and machine learning systems. Moreover, the interaction between human and algorithmic bias increases the likelihood of suboptimal decisions, especially in forecasting and data-driven contexts. The research also highlights that the negative impact of bias can be effectively minimized through the implementation of prevention frameworks, including debiasing strategies, explainable AI, human-in-the-loop approaches, and multi-objective optimization, which collectively enhance transparency, accountability, and decision quality. This research contributes to the literature by providing a comprehensive synthesis of foresight bias and decision accuracy, while offering practical insights for improving decision-making in complex and digitalized environments.

INTRODUCTION

Decision accuracy is a fundamental aspect across various contexts, ranging from strategic management and artificial intelligence (AI) systems to data-driven decision-making, because accurate decisions play an important role in improving organizational performance, reducing uncertainty, and supporting the effective achievement of goals (Kovari, 2024; Paolanti et al., 2024). However, the literature shows that the decision-making process is not completely rational, but is often influenced by various cognitive and systemic biases arising from both humans and technology (Ferrara, 2024; Berthet, 2022). This condition causes deviations between decisions made and optimal decisions, thereby reducing the overall quality of decision-making.

In an organizational context, cognitive bias has proven to be a major factor influencing the quality of strategic decisions. Empirical research shows that managers often experience the illusion of control bias, which refers to the tendency to overestimate their ability to control decision outcomes, ultimately leading to irrational and risky decisions (Midtgård & Selart, 2025). In addition, biases such as overconfidence have also become dominant across various professions, including management, finance, law, and medicine, reinforcing individuals' tendencies to make non-objective decisions (Berthet, 2022). Thus, cognitive bias is a crucial factor explaining why decision-making often fails to reflect rational and accurate evaluations.

On the other hand, technological developments, especially in artificial intelligence (AI), big data, and explainable AI (XAI), have opened opportunities to improve decision-making quality through more comprehensive and systematic data analysis. Studies show that the integration of these technologies can reduce bias and improve decision accuracy through more objective information processing (Theodorakopoulos et al., 2025). However, technology is not entirely free from bias, as biases can arise from historical data, algorithm design, and human intervention during the system development process (Siddique et al., 2023; Ferrara, 2024). Therefore, the use of AI in decision-making presents a paradox in which technology can serve both as a solution and as a new source of bias.

The machine learning literature shows that bias can appear at all stages of the process, from data collection and preprocessing to model evaluation, resulting in systematic yet inaccurate decisions (Siddique et al., 2023). This bias often originates from historical data reflecting previous human decision-making patterns, which are subsequently replicated and even reinforced by algorithms (Alelyani, 2021; Vieira et al., 2025). In this context, bias is not only a technical problem, but also a structural issue related to fairness, discrimination, and decision validity.

To address these problems, various bias mitigation approaches have been developed in the literature. In general, these approaches can be categorized into two main strategies, namely debiasing and choice architecture, both of which aim to reduce distortions in the decision-making process at the individual and system levels (Fasolo et al., 2024). In the context of machine learning, bias mitigation strategies also include preprocessing, in-processing, and post-processing techniques designed to reduce bias in data and models (Siddique et al., 2023). In addition, multi-objective optimization-based approaches suggest that fairness and accuracy can be improved simultaneously despite trade-offs between the two (Nagpal et al., 2024; Kondapalli et al., 2025).

Furthermore, research shows that decision accuracy depends not only on technical aspects, but also on factors such as transparency, explainability, and fairness in AI systems. These three aspects represent the main dimensions in building trust in technology-based decision-making systems (Paolanti et al., 2024). Other approaches, such as the use of synthetic data, have also been shown to improve fairness and accuracy by addressing data imbalances, although their effectiveness is highly dependent on the quality of the generated data (Hameed et al., 2024).

In more complex contexts, such as forecasting and dynamic systems, bias also emerges in the form of prediction errors that increase over time. Research shows that the use of ensemble models and bias-correction techniques can significantly improve the accuracy of long-term predictions (Wang et al., 2025; Tudaji et al., 2025). In addition, the human-in-the-loop approach has proven effective in improving system fairness and adaptability by involving humans in the process of evaluating and adjusting models (Van Busum & Fang, 2025).

Although the literature on bias, decision accuracy, and bias mitigation has grown rapidly, most studies remain fragmented and focus on specific aspects, such as human cognitive bias or bias in machine learning, without integrating the two into a comprehensive conceptual framework (Pagano et al., 2023). In addition, research on bias in the context of foresight or future prediction remains relatively limited, even though bias in foresight can significantly affect the quality of long-term decisions. These limitations indicate a research gap in integrating different types of biases and their mitigation strategies into a holistic framework (Fasolo, Heard, & Scopelliti, 2025).

Based on this background, this study aims to conduct a Systematic Literature Review (SLR) of the literature related to foresight bias, decision accuracy, and various prevention frameworks that have been developed. The SLR approach is used to systematically identify, synthesize, and evaluate findings from previous studies to develop a more comprehensive understanding of the relationship between bias, decision accuracy, and mitigation strategies. Thus, this research is expected to contribute theoretically to the development of the literature on bias and decision-making, as well as practically to the development of frameworks capable of improving decision accuracy across various complex and digitized contexts.

RESEARCH METHOD

This study uses the Systematic Literature Review (SLR) method with reference to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to systematically identify, select, evaluate, and synthesize various relevant scientific publications related to foresight bias, decision accuracy, and prevention frameworks. This approach was chosen because it allows the literature review process to be carried out in a structured, transparent, and replicative manner, so that the results of the study are not only descriptive, but also analytical in identifying patterns of relationships between variables and the development of previous research. Use of the SLR is considered effective in integrating various empirical and conceptual findings scattered in the literature related to bias and decision-making (Pagano et al., 2023; Theodorakopoulos et al., 2025).

The literature in this study comes from internationally reputable scientific articles that are relevant to the topics of decision-making, cognitive bias, foresight bias, artificial intelligence, machine learning bias, and bias mitigation frameworks. The literature used includes articles indexed in international journals (Scopus Q1–Q3) with diverse methodological approaches, such as experiments, empirical surveys, systematic reviews, and conceptual studies. In substance, the literature analyzed shows that bias in decision-making is a multidimensional phenomenon that involves the interaction between human cognitive factors, data quality, and technology system design (Ferrara, 2024; Siddique et al., 2023).

In line with these data sources, this study focuses on the analysis on 20 main articles that have been previously mapped. The articles cover a wide range of research approaches relevant to the topics of foresight bias and decision accuracy, including experimental studies, empirical surveys, as well as literature reviews that discuss bias in AI-based systems and human decision-making. The focus of the literature is not only limited to one type of bias, but also includes a variety of interrelated biases such as overconfidence, illusion of control bias, algorithmic bias, and forecasting bias, as the literature shows that these different types of bias interact with each other in influencing decision accuracy (Midtgård & Selart, 2025; Wang et al., 2025).

To obtain relevant and quality articles, the literature selection process is carried out through several systematic stages. The first stage is identification, which is a literature search using keywords related to the research topic, such as "foresight bias", "decision accuracy", "cognitive bias in decision making", "AI bias", "machine learning bias", "bias mitigation", and "decision support systems". These keywords were chosen because they represent the main dimensions of the research, namely bias in future predictions, decision accuracy, and bias mitigation strategies in decision-making systems.

The second stage is screening, which is the filtering of articles based on titles, abstracts, and keywords to ensure compatibility with the research topic. At this stage, articles that are not related to decision-making, do not explicitly discuss bias, or focus only on technical aspects unrelated to decision accuracy are excluded from the selection process. The third stage is the eligibility assessment, which is a thorough evaluation of the content of the article to ensure that each article has a relevant contribution to the research. Articles are defended when they meet the inclusion criteria, namely: (1) discussing bias in decision-making or predictive systems; (2) examine the implications of bias on decision accuracy; (3) describe mitigation strategies or prevention frameworks; and (4) use a clear and accountable methodology.

Based on these stages, 20 articles were obtained as a final sample that was analyzed in depth. The articles were then codified and grouped into several main themes, namely: (1) foresight bias in decision-making; (2) the effect of bias on decision accuracy; (3) bias in systems based on artificial intelligence and machine learning; (4) prevention frameworks in bias mitigation; and (5) bias in forecasting and complex systems. This thematic categorization is important because the literature shows that bias does not only appear in one dimension, but is a complex phenomenon involving interactions between humans, data, and technology (Siddique et al., 2023; Paolanti et al., 2024).

All articles that have passed the selection are then analyzed using a qualitative thematic analysis approach, namely by identifying patterns of findings, comparing results between studies, and compiling conceptual synthesis related to the relationship between foresight bias, decision accuracy, and prevention frameworks. The analysis also considers the context of the research, such as the type of method, the field of application, and the role of technology in the decision-making process. Thus, the SLR method in this study not only maps the existing literature, but also provides a more comprehensive understanding of how bias affects decision accuracy as well as how mitigation strategies can be developed more effectively in various complex and digitized contexts.

RESULTS AND DISCUSSION

The distribution of journal quality shows that most of the articles analyzed in the study of foresight bias, decision accuracy, and prevention frameworks come from highly reputable journals. Of the total 20 articles, 10 articles (50%) came from the Scopus Q1 journal, followed by 6 articles (30%) from Scopus Q2, and 4 articles (20%) from Scopus Q3. This composition shows that the literature used has strong methodological quality and has gone through a rigorous peer-review process. The dominance of Q1 journals also indicates that the topic of bias in decision-making and AI-based systems is an issue that receives high attention in global research.

Table 1. Journal Index Distribution

Journal Index	Number of Articles	Percentage
Scopus Q1	10	50%
Scopus Q2	6	30%
Scopus Q3	4	20%
Total	**20**	**100%**

Source: Author's analysis based on 20 reviewed articles, 2025

Based on the synthesis of the literature, research on foresight bias and decision accuracy shows that the phenomenon of bias in decision-making cannot be explained from just one perspective, but requires a multidisciplinary approach which includes cognitive psychology, data science, and artificial intelligence systems. Most studies use theories such as bounded rationality, behavioral decision theory, and heuristics and biases to explain how human and system limitations affect the quality of decisions. This shows that bias is the result of a complex interaction between human factors, data, and technology.

Table 2. Distribution of Research Theories

Research Theory	Number of Articles	Percentage
Bounded Rationality Theory	5	25%
Behavioral Decision Theory	4	20%
Heuristics and Biases Theory	3	15%
Machine Learning Theory	3	15%
Decision Support Theory	2	10%
Others	3	15%
Total	**20**	**100%**

Source: Author's analysis based on 20 reviewed articles, 2025

The distribution of research methods shows that experimental and quantitative approaches are still the dominant methods in the study of bias and decision accuracy. A total of 8 articles (40%) used experimental or quantitative methods, followed by 7 articles (35%) using literature review or SLR, and 3 articles (15%) using a qualitative approach. Meanwhile, 2 articles (10%) used a mixed methods approach. This suggests that biased research tends to examine decision-making behavior in controlled conditions as well as through data-driven system analysis.

Table 3. Distribution of Research Methods

Journal Index	Number of Articles	Percentage
Experimental/Quantitative	8	**40%**
Literature Review / SLR	7	**35%**
Qualitative	3	**15%**
Mix Method	2	**10%**
Total	**20**	**100%**

Source: Author's analysis based on 20 reviewed articles, 2025

The distribution of research focus shows that most of the articles focus on the relationship between bias and decision accuracy, which is as many as 8 articles (40%). In addition, 5 articles

(25%) discussed bias in artificial intelligence and machine learning systems, 4 articles (20%) reviewed prevention frameworks, and 3 articles (15%) discussed bias in forecasting and complex systems. This shows that the research focuses not only on human behavior, but also on the integration of technology in the decision-making process.

Table 4. Research Focus Distribution

Journal Index	Number of Articles	Percentage
Bias & Decision Accuracy	8	40%
AI & Machine Learning Bias	5	25%
Prevention Frameworks	4	20%
Forecasting & Complex Systems	3	15%
Total	**20**	**100%**

Source: Author's analysis based on 20 reviewed articles, 2025

The distribution of research results shows that most studies conclude that foresight bias and other biases have a negative impact on decision accuracy. A total of 9 articles (45%) showed that bias decreases decision accuracy, especially in complex and uncertain conditions. In addition, 5 articles (25%) showed that bias in AI systems can amplify decision errors due to biased historical data. A total of 4 articles (20%) showed that the use of prevention frameworks can improve decision accuracy, while 2 articles (10%) showed that bias can be minimized through the integration of people and technology.

Table 5. Main Research Results

Main Research Results	Number of Articles	Percentage
Bias lowers decision accuracy	9	45%
Bias in AI reinforces decision errors	5	25%
Prevention frameworks Improve accuracy	4	20%
Human-AI integration reduces bias	2	10%
Total	**20**	**100%**

Source: Author's analysis based on 20 reviewed articles, 2025

In general, the results show that foresight bias is a significant factor that affects the quality of decision-making, especially in the context of future predictions and technology-based systems. This bias causes distortions in the interpretation of information and long-term outcome estimation, thereby reducing decision accuracy. In addition, the existence of bias does not only come from humans, but also from artificial intelligence systems that utilize historical data, thereby expanding the complexity of problems in modern decision-making.

However, the literature also shows that the impact of bias is not absolute and can be minimized through various prevention frameworks. Approaches such as debiasing, explainable AI, human-in-the-loop, and mitigation techniques in machine learning have been proven to improve the quality of decisions. Thus, bias management is a crucial aspect in improving decision accuracy, especially in a complex, dynamic, and digitalized environment.

Foresight Bias as a Determinant of Decline in Decision Accuracy

Based on the synthesis of the literature, foresight bias is a form of cognitive bias that has a significant influence on decision accuracy, especially in the context of future-oriented decision-making. This bias arises when individuals or systems rely too much on past experiences, historical patterns, or initial assumptions in predicting uncertain conditions. In complex and uncertain situations, limitations in processing future information cause individuals to tend to simplify assessments through a heuristic approach, so that the evaluation process becomes not entirely objective and tends to ignore relevant alternatives.

Furthermore, foresight bias not only impacts prediction errors, but also affects the overall decision-making structure. Individuals who get caught up in this bias tend to reinforce initial beliefs and ignore new information that contradicts previous expectations. This causes decisions to become less adaptive to environmental changes, increasing the risk of errors in strategic planning. In the context of organizations, this condition can have an impact on the quality of policies and strategies taken, especially in the face of market dynamics and global uncertainty.

These findings are in line with research showing that biases such as overconfidence and illusion of control bias reinforce an individual's tendency to overconfidence in the predictions generated, thereby lowering the accuracy of decisions (Midtgård & Selart, 2025; Berthet, 2022). Thus, foresight bias is not only an individual's cognitive limitation, but also a systemic factor that affects the quality of decisions in a variety of contexts. Therefore, understanding this bias is important to improve decision accuracy, especially in long-term decision-making.

The Interaction of Cognitive Bias and AI Systems in Decision Making

The literature shows that bias in decision-making comes not only from humans, but also from artificial intelligence (AI)-based systems and machine learning. In this context, biases in AI systems can arise from a variety of sources, including unrepresentative historical data, non-neutral algorithm designs, as well as model training processes that do not adequately consider fairness aspects (Ferrara, 2024; Siddique et al., 2023). As a result, AI systems can produce decisions that look technically objective, but contain distortions that affect the accuracy of the decision.

The interaction between human bias and system bias creates new complexities in modern decision-making processes. In many cases, users tend to trust the output of AI systems without conducting critical evaluations, resulting in a phenomenon of dependence on technology. This condition causes the biases emanating from the system to be not only accepted, but also reinforced by the user. In addition, human cognitive biases such as confirmation bias and overreliance can magnify the impact of algorithmic bias, resulting in decisions that deviate further from optimal conditions.

This shows that while AI has great potential in improving decision accuracy, it cannot stand alone without adequate human control. Therefore, AI-driven decision-making requires a balance between technological capabilities and critical human evaluation. Thus, the integration between humans and systems is key in reducing bias and improving the quality of decisions in an increasingly digitized environment.

The Impact of Bias on Decision Accuracy in Complex Systems

One of the key findings of the study is that bias, including foresight bias, has a direct impact on declining decision accuracy, especially in complex systems such as forecasting and data-driven decision-making. In such systems, bias not only affects the interpretation of information, but also impacts the quality of the predictions produced. When bias is not controlled, errors in predictions can increase significantly, especially over longer time horizons (Wang et al., 2025).

In addition, in complex systems, bias tends to be cumulative, where small errors in the early stages can develop into larger deviations over time. This shows that decision accuracy is greatly influenced by the system's ability to manage bias in an ongoing manner. In this context, Prediction errors are caused not only by data limitations, but also by the interaction between cognitive bias and the limitations of models in capturing complex system dynamics.

Furthermore, the complexity of the system also increases uncertainty in decision-making, thereby magnifying the potential for bias. Therefore, bias control is a key factor in improving the quality of decisions in a dynamic system. Thus, an approach that integrates data management, models, and human intervention is needed to ensure that decision accuracy can be continuously improved.

The Role of Prevention Frameworks in Reducing Bias

The results of the literature synthesis show that bias in decision-making is not an uncontrollable phenomenon, but can be minimized through the application of various prevention frameworks. Approaches such as debiasing and choice architecture play an important role in reducing distortions in the process of evaluating information and selecting alternative decisions (Fasolo et al., 2024). This strategy focuses not only on changing individual behavior, but also on designing systems that are able to support more rational and objective decision-making.

In the context of technology, various bias mitigation techniques have been developed in machine learning, such as preprocessing, in-processing, and post-processing, which aim to reduce bias in data and models (Siddique et al., 2023). In addition, a multi-objective optimization-based approach shows that fairness and accuracy can be optimized simultaneously despite the trade-offs between the two (Nagpal et al., 2024). This shows that improving decision accuracy depends not only on technical accuracy, but also on the balance between fairness and system performance.

Furthermore, approaches such as explainable AI, human-in-the-loop, and increased transparency and accountability of systems are important elements in reducing bias and improving the quality of decisions (Paolanti et al., 2024). With a transparent and explainable system, users can critically evaluate the output produced. Therefore, prevention frameworks not only serve as a bias mitigation tool, but also as a mechanism to improve trust and quality of decision-making in a complex and digitized environment.

Research Limitations

This study has several limitations that need to be considered in the interpretation of the results. First, the number of articles analyzed was limited to 20 studies, so it did not fully represent all research developments related to foresight bias and decision accuracy. Second, there are variations in methods, research contexts, and areas of application that can affect the consistency of findings. Third, most studies still use experimental and model-based approaches, so they do not fully reflect real-world conditions in decision-making practices.

Practical and Theoretical Implications

Theoretically, this study strengthens the literature on decision-making by emphasizing that decision accuracy is not only influenced by technical aspects, but also by the interaction between cognitive biases and technological systems. The study also expands the concept of bounded rationality by integrating the role of biased foresight in modern AI-based contexts.

Practically, the results of this study provide implications for organizations and system developers to improve the quality of decisions through the implementation of prevention frameworks. This includes strengthening debiasing strategies, the use of transparent and explainable systems, and human integration in the decision-making process. Thus, organizations can improve decision accuracy while minimizing the risk of errors in a complex and digitized environment.

CONCLUSION

Based on the results of the Systematic Literature Review (SLR) of 20 scientific articles, it can be concluded that foresight bias is one of the main factors that affect the decline in decision accuracy, especially in the context of long-term decision-making and technology-based systems. This bias causes distortions in future predictions, so the resulting decisions do not fully reflect optimal conditions. In addition, this study shows that bias does not only come from humans, but also from artificial intelligence systems that use historical data, thus expanding the complexity of the problem in modern decision-making. Nonetheless, the literature suggests that the impact of bias can be minimized through various prevention frameworks, such as debiasing, explainable AI, and human-in-the-loop integration. Therefore, bias management is a crucial aspect in improving the quality and accuracy of decisions in a complex and digitized environment. For future research, it is recommended to conduct empirical studies that test the effectiveness of specific prevention frameworks in real-world organizational settings, as well as to explore the integration of bias mitigation techniques across both human and AI decision-makers simultaneously. Practically, organizations should adopt structured debiasing protocols, invest in explainable AI systems, and regularly audit decision outcomes to identify and correct bias dynamically.

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