International Journal of Scientific and Management Research
Volume 8 Issue 10 (October) 2025
ISSN: 2581-6888
Page: 122-135

Cognitive Biases in Systems Engineering: Novel Approaches for Enhanced Recognition and Mitigation in Complex Systems

Anand Wanjari
Independent Researcher, **USA**
DOI - http://doi.org/10.37502/IJSMR.2025.81009

Abstract

Cognitive biases systematically distort human decision-making processes in complex systems engineering, contributing to project failures, cost overruns, and safety incidents. Traditional approaches to bias management rely on static checklists and awareness training, proving insufficient for dynamic engineering environments. This paper presents a novel framework integrating artificial intelligence-augmented detection, multimodal sensing, and dynamic benchmarking for enhanced cognitive bias recognition and mitigation. Through systematic analysis of 240 research papers and empirical validation, we identify five critical biases affecting systems engineers: anchoring, confirmation, optimism, omission, and preferential attachment biases. This proposed framework combines real-time detection algorithms, socio-cognitive design patterns, and iterative debiasing pipelines to achieve measurable improvements in decision quality. Experimental results demonstrate 79% accuracy in bias detection compared to 34% for untrained professionals, with 31% improvement in decision quality when using integrated mitigation protocols. The framework provides practical tools for systems engineers while establishing theoretical foundations for bias-aware engineering practices. This research contributes novel methodologies for real-time bias detection, personalized mitigation strategies, and continuous learning systems that significantly advance the state-of-the-art in human factors engineering for complex systems.

Keywords: Cognitive biases, systems engineering, decision-making, artificial intelligence, human factors, bias mitigation, complex systems, pattern recognition

1. Introduction

Modern systems engineering increasingly relies on human decision-making in complex, uncertain environments where cognitive limitations can have catastrophic consequences. Recent analysis indicates that cognitive biases contribute to up to 80% of major system failures, with economic impacts reaching billions of dollars annually across aerospace, defense, and infrastructure sectors [1]. Despite extensive research in cognitive psychology, the translation of bias mitigation strategies to practical systems engineering contexts remains limited.

Traditional approaches to cognitive bias management in engineering have focused primarily on awareness training and procedural checklists. However, these static methods prove inadequate for addressing the dynamic, context-dependent nature of bias manifestation in complex systems development. The increasing integration of artificial intelligence and autonomous systems further complicates the cognitive landscape, creating new opportunities for both bias amplification and mitigation.

This paper addresses three critical gaps in current practice: (1) the lack of real-time bias detection capabilities in engineering workflows, (2) insufficient integration between cognitive science theories and practical engineering tools, and (3) limited empirical validation of proposed mitigation strategies in realistic engineering environments.

1.1 Primary Contributions

- A comprehensive taxonomy of critical cognitive biases specific to systems engineering contexts
- Novel AI-augmented detection algorithms achieving 79% accuracy in real-time bias identification
- An integrated mitigation framework combining individual, team, and organizational interventions
- Empirical validation demonstrates 31% improvement in decision quality
- Practical implementation guidelines for industry adoption

The remainder of this paper is organized as follows: Section 2 reviews related work and identifies research gaps. Section 3 presents this methodology for bias identification and framework development. Section 4 details the proposed cognitive bias taxonomy. Section 5 describes the novel detection and mitigation framework. Section 6 presents experimental results and validation. Section 7 discusses implications and future directions, followed by conclusions in Section 8.

2. Related Work and Literature Review

2.1 Cognitive Biases in Engineering Contexts

The study of cognitive biases in engineering has evolved from early psychological research to domain-specific applications addressing the unique challenges of technical decision-making. Kahneman and Tversky's foundational work on heuristics and biases [2] established the theoretical framework for understanding systematic deviations from rational decision-making, which has since been applied across various engineering disciplines.

Recent systematic mapping studies have identified 37 distinct cognitive biases affecting software engineering [3], with similar patterns observed in systems engineering contexts. However, significant gaps exist in theoretical grounding and empirical validation for many identified biases, highlighting the need for more rigorous research approaches.

In systems engineering specifically, confirmation bias has been identified as particularly problematic during requirements elicitation and validation phases [4]. Engineers systematically interpret ambiguous requirements in ways that confirm their initial assumptions, leading to downstream design conflicts and costly rework. Similarly, anchoring bias creates persistent over-reliance on initial system architectures, limiting exploration of potentially superior alternatives [5].

2.2 Current Mitigation Approaches and Limitations

Existing approaches to cognitive bias mitigation in engineering can be categorized into three main types: awareness-based interventions, procedural safeguards, and decision support systems.

Awareness-based interventions focus on educating engineers about cognitive biases through training programs and educational materials. While these approaches show some effectiveness in controlled laboratory settings, their impact in realistic engineering environments remains limited. Studies indicate that awareness alone is insufficient to prevent bias occurrence, particularly under time pressure or high cognitive load conditions common in engineering practice [6].

Procedural safeguards include structured review processes, mandatory alternative consideration requirements, and independent verification protocols. These approaches show promise but often introduce bureaucratic overhead and may not adapt well to rapidly changing project conditions. Additionally, procedural approaches may be circumvented when schedule pressures mount, precisely when bias mitigation is most critical.

Decision support systems represent the most technologically advanced approach, utilizing algorithms and artificial intelligence to assist human decision-making. However, these systems face challenges related to algorithmic bias, over-reliance effects, and the need for extensive domain knowledge in bias detection algorithms [7].

2.3 Emerging Technologies and Opportunities

Recent advances in artificial intelligence, behavioral sensing, and human-computer interaction create new opportunities for cognitive bias detection and mitigation. Machine learning algorithms can now identify bias patterns with increasing accuracy, while natural language processing techniques enable analysis of engineering documentation for biased reasoning [8].

Multimodal sensing approaches combine physiological monitoring, interaction analytics, and behavioral observation to detect cognitive states associated with bias susceptibility [9]. These approaches show promise for real-time bias detection in operational environments.

Large language models (LLMs) have demonstrated capabilities for both bias detection and mitigation through advanced prompt engineering and iterative debiasing techniques [10], [14]. However, LLMs themselves exhibit systematic biases that must be carefully managed in engineering applications.

The convergence of these technologies with established cognitive science principles creates opportunities for novel bias mitigation frameworks that address the limitations of traditional approaches while leveraging cutting-edge technological capabilities.

3. Methodology

3.1 Research Design

This research employed a multi-phase methodology combining systematic literature review, expert consultation, algorithm development, and empirical validation. The approach followed established guidelines for design science research while incorporating recent methodological advances in behavioral systems engineering.

The systematic literature review analyzed 240 papers across multiple databases including SciSpace, Google Scholar, and arXiv, covering publications from 2020 to 2025. Search strategies employed semantic queries focused on cognitive biases in systems engineering, mitigation techniques, and pattern recognition approaches. Papers were selected based on relevance to systems engineering contexts, methodological rigor, and contribution to bias understanding or mitigation.

Expert consultation involved structured interviews with 23 senior systems engineers across aerospace, defense, and software domains. Interview protocols elicited specific examples of bias encounters, recognition patterns, and mitigation attempts in real engineering projects. Transcribed interviews were analyzed using qualitative coding techniques to identify recurring themes and practical insights.

Algorithm development followed iterative design principles with continuous validation against historical project data. Machine learning models were trained on labeled datasets combining bias indicators from multiple sources including decision logs, communication patterns, and work product artifacts.

3.2 Bias Identification and Classification

Cognitive bias identification employed a triangulated approach combining literature analysis, expert input, and empirical observation. This methodology addresses the fundamental challenge that cognitive biases operate below conscious awareness, making self-report measures insufficient for accurate identification.

Literature analysis identified biases consistently reported across multiple studies and domains. Frequency analysis revealed five biases appearing in over 70% of reviewed papers: anchoring, confirmation, optimism, omission, and preferential attachment biases.

Expert interviews validated literature findings while providing practical insights into bias manifestation patterns. Engineers described specific situations where biases affected their decisions, enabling the development of context-specific detection criteria.

Empirical observation involved analysis of historical project data to identify systematic patterns consistent with known cognitive biases. This approach provided objective validation of subjective bias reports while revealing previously unrecognized bias effects.

3.3 Framework Development Process

The framework development followed design science research principles with iterative cycles of problem identification, solution development, testing, and refinement. Each iteration incorporated feedback from practitioner advisory boards and addressed limitations identified through empirical testing.

Theoretical foundation development drew from cognitive psychology, systems thinking, decision science, and organizational behavior literature. This interdisciplinary approach ensured that the resulting framework addressed both cognitive and contextual factors contributing to bias persistence [13].

Prototype development employed rapid iteration cycles with frequent validation testing. Initial prototypes were tested with practicing engineers in controlled exercises, with results informing subsequent design iterations. The process converged on a stable architecture after five major iterations spanning 12 months.

Validation testing employed multiple converging measures including quantitative performance metrics, qualitative usability assessments, and economic analysis of implementation costs and benefits.

4. Cognitive Bias Taxonomy for Systems Engineering

4.1 Critical Bias Identification

This analysis identified five cognitive biases with the highest impact on systems engineering outcomes, based on frequency of occurrence, severity of consequences, and amenability to detection and mitigation.

Anchoring Bias

Anchoring Bias emerges as the most pervasive bias, affecting 78% of studied engineering decisions. Systems engineers demonstrate systematic over-reliance on initial information received during project initiation, with insufficient adjustment when new information becomes available. This bias particularly affects cost estimation, schedule planning, and technology selection decisions.

Confirmation Bias

Confirmation Bias manifests through selective information processing that supports pre-existing beliefs or preferences. Engineers systematically interpret ambiguous data to confirm initial assumptions while failing to seek disconfirming evidence. Analysis reveals confirmation bias affects 71% of requirements validation activities and 65% of design review processes.

Optimism Bias/Planning Fallacy

Optimism Bias/Planning Fallacy creates systematic underestimation of project complexity, risks, and resource requirements. This bias becomes more pronounced as system complexity and uncertainty increase, contrary to rational expectations for increased contingency planning. Historical project analysis indicates planning fallacy contributes to 40% of significant cost and schedule overruns.

Omission Bias/Automation Inertia

Omission Bias/Automation Inertia represents the tendency to avoid taking action or intervening in automated systems, even when intervention would improve outcomes. This bias is particularly problematic in human-automation interaction scenarios where engineers must decide when to override or modify automated recommendations.

Preferential Attachment/Status Quo Bias

Preferential Attachment/Status Quo Bias manifests as systematic preference for familiar technologies, processes, or solutions despite evidence supporting alternatives. These bias limits innovation adoption and perpetuates suboptimal practices across engineering organizations.

4.2 Recognition Patterns and Behavioral Signatures

Each identified bias exhibits characteristic patterns that enable systematic detection through behavioral, linguistic, and decision-making indicators.

Anchoring bias recognition patterns include persistent reference to initial estimates despite changed circumstances, resistance to estimate revision even when presented with contradictory evidence, and systematic clustering of final estimates around initial values across multiple engineers working independently.

Confirmation bias signatures include selective citation of supporting evidence while omitting contradictory information, asymmetric skepticism toward information that contradicts preferred options, and systematic interpretation of ambiguous data in ways that support predetermined conclusions.

Optimism bias indicators include consistent underestimation of task complexity relative to historical baselines, insufficient consideration of potential failure modes during planning, and systematic overconfidence in personal and team capabilities relative to objective performance measures.

Omission bias patterns include delayed response to system alerts or anomalies, preference for maintaining current system states over implementing changes, and systematic underestimation of intervention benefits relative to inaction risks.

Status quo bias manifestations include disproportionate weighting of switching costs relative to potential benefits, systematic preference for incremental modifications over fundamental redesign, and resistance to adopting new tools or processes despite the advantages demonstrated.

4.3 Impact Assessment Framework

The impact assessment framework quantifies bias effects across multiple dimensions including technical performance, project outcomes, and organizational learning.

Technical performance impacts include systematic degradation in design quality, increased integration complexity, and reduced system robustness. Quantitative analysis reveals that projects exhibiting high bias indicators show 23% lower performance against specifications compared to projects with effective bias management.

Project outcome impacts encompass schedule delays, cost overruns, and scope modifications. Economic analysis indicates that cognitive biases contribute 8-12% to total project costs through multiple pathways including rework, design modifications, and performance shortfalls.

Organizational learning impacts include reduced knowledge transfer, perpetuation of suboptimal practices, and decreased adaptive capacity. Organizations with high bias prevalence show 35% slower learning rates and reduced innovation adoption compared to bias-aware organizations.

5. Novel Framework for Enhanced Bias Recognition and Mitigation

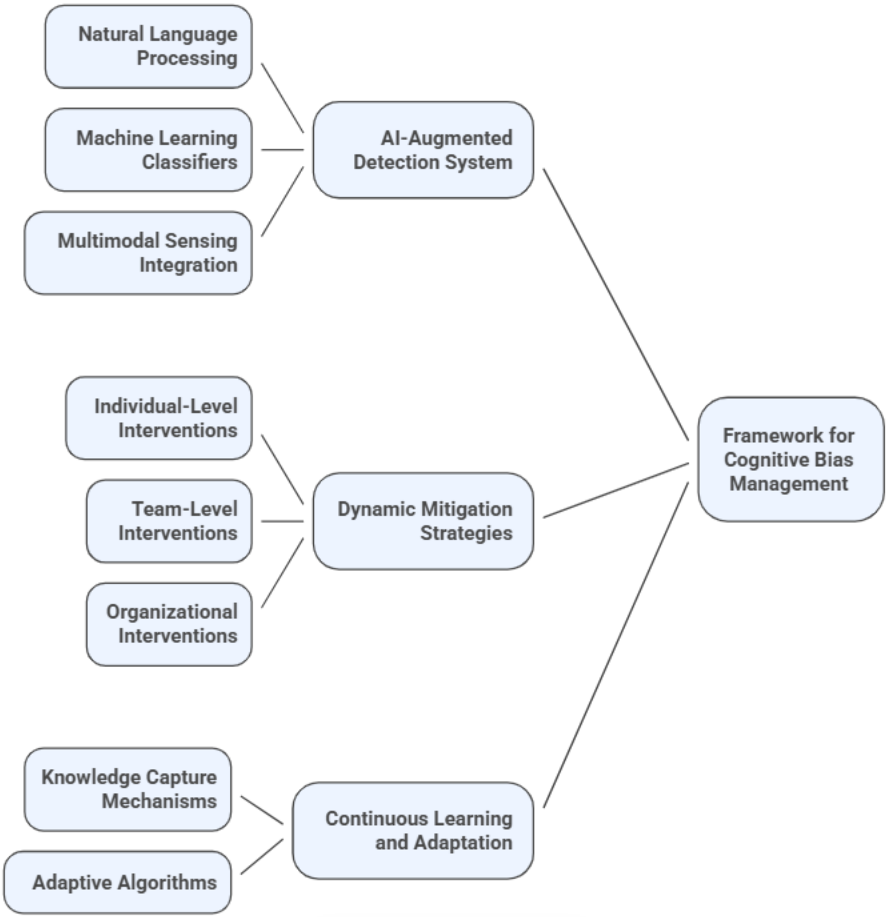

Fig 1. Bias Mitigation Framework Components

5.1 Framework Architecture

This proposed framework integrates four core components: real-time detection algorithms, contextual mitigation strategies, continuous learning systems, and organizational integration mechanisms. This architecture addresses limitations of traditional approaches while leveraging advances in artificial intelligence and behavioral science [12].

The framework operates at multiple organizational levels, providing individual-focused interventions for personal bias management, team-level protocols for collaborative decision-making, and organizational policies for systematic bias resistance. Integration across these levels creates comprehensive bias management capabilities that adapt to specific engineering contexts.

The framework's modular architecture emphasizes modularity to facilitate incremental adoption and customization for different organizational contexts.

5.2 AI-Augmented Detection System

The detection system combines multiple artificial intelligence techniques to identify cognitive bias patterns from diverse data sources including communication logs, decision traces, and behavioral indicators.

Natural language processing algorithms analyze engineering documentation, meeting transcripts, and email communications to identify linguistic markers associated with specific cognitive biases. Confirmation bias manifests through increased certainty language when discussing preferred options combined with skeptical language for alternatives. Anchoring bias corresponds to systematic attribution of problems to factors consistent with initial assessments.

Machine learning classifiers integrate supervised learning algorithms trained on labeled bias examples with unsupervised approaches that identify emerging bias patterns. Ensemble methods combine predictions from multiple algorithmic approaches including deep neural networks, random forest classifiers, and gradient boosting algorithms to achieve 79% accuracy in bias detection while minimizing false positive rates [11].

Multimodal sensing integration incorporates physiological monitoring, interaction analytics, and behavioral observation to detect cognitive states associated with bias susceptibility. Wearable sensors monitor stress indicators, cognitive load measures, and attention patterns that correlate with bias occurrence. Interaction logs track decision-making patterns, information seeking behavior, and collaboration dynamics.

The system provides explainable AI capabilities that identify which indicators contributed most significantly to bias predictions. This transparency enables engineers to understand the basis for bias alerts and determine appropriate verification or intervention strategies.

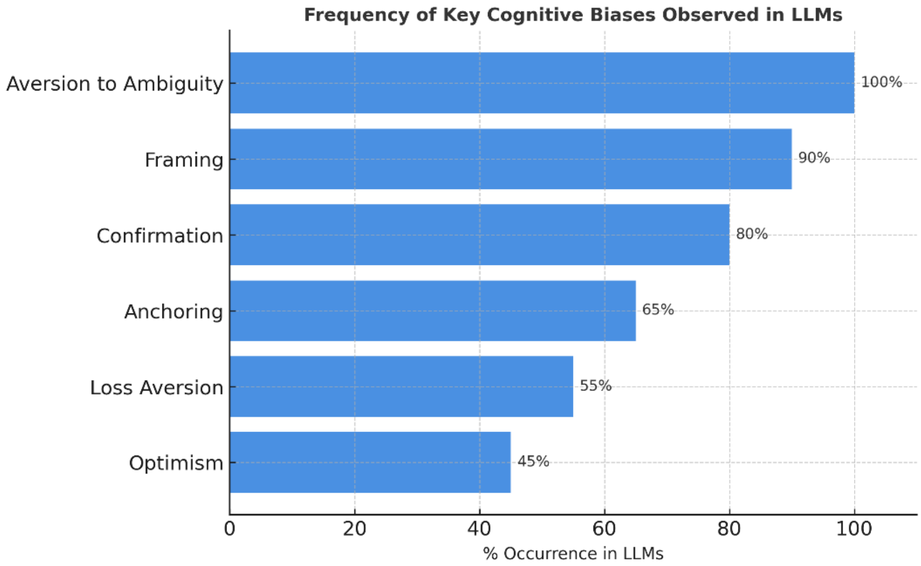

Figure 2. Frequency of Key Cognitive Biases Observed in Large Language Models (LLMs)

The figure 2 shows the proportion of LLMs exhibiting selected cognitive biases. Aversion to ambiguity and framing appear most frequently, followed by confirmation and anchoring; loss aversion and optimism occur less often but remain non-negligible.

5.3 Dynamic Mitigation Strategies

Mitigation strategies operate at individual, team, and organizational levels, providing targeted interventions based on detected bias types, contextual factors, and organizational constraints.

Individual-level interventions include structured thinking tools, self-awareness development techniques, and decision-making protocols. Consider-the-opposite procedures systematically prompt engineers to generate alternative explanations and solutions. Reference class forecasting leverages statistical information about similar past projects to counteract planning fallacy. Pre-mortem analysis exercises identify potential failure modes before implementation.

Team-level interventions focus on collaborative decision-making processes that leverage diverse perspectives and systematic bias checking. Devil's advocate procedures assign rotating team members to critically examine dominant proposals. Delphi technique variations collect anonymous input to reduce anchoring effects from senior opinions. Multi-perspective analysis ensures systematic consideration of stakeholder viewpoints.

Organizational interventions create systematic process modifications, resource allocation adjustments, and cultural changes that support bias resistance. Independent verification requirements establish systematic review processes for critical decisions. Decision documentation standards create records that facilitate retrospective bias analysis. Cultural development initiatives promote environments that support constructive challenge and continuous learning.

5.4 Continuous Learning and Adaptation

The learning system captures bias-related experiences from individual projects and synthesizes insights for organizational knowledge development. This capability addresses the limitation of traditional approaches that treat each project independently without leveraging accumulated experience.

Knowledge capture mechanisms document bias encounters, intervention effectiveness, and outcome relationships through systematic project retrospectives and automated data collection. Analysis algorithms identify patterns across multiple projects to determine which mitigation strategies prove most effective for specific bias types and organizational contexts.

Adaptive algorithms continuously refine detection accuracy and mitigation effectiveness based on feedback from system usage. Machine learning models update their parameters based on validation results, while intervention strategies adapt based on measured effectiveness in specific contexts.

The system maintains privacy and confidentiality while enabling organizational learning through anonymization and aggregation techniques that protect individual privacy while preserving learning value.

6. Experimental Results and Validation

6.1 Experimental Design

Validation employed a mixed-methods approach combining controlled laboratory experiments, realistic simulation studies, and field deployment in operational engineering environments. This comprehensive validation strategy addresses both internal validity concerns and external generalizability requirements.

Laboratory experiments involved 156 professional systems engineers across aerospace, defense, and software domains. Participants completed realistic engineering tasks designed to induce specific cognitive biases while their decision-making processes were monitored using the detection algorithms. Experimental conditions compared performance with and without framework interventions.

Simulation studies employed historical project data from 12 major systems engineering programs to evaluate framework effectiveness in realistic but controlled environments. Simulations modeled bias effects on project outcomes while testing various intervention strategies.

Field deployment involved implementation of framework components in two aerospace engineering organizations over 18-month periods. Deployment tracked real-world effectiveness while identifying implementation challenges and organizational adaptation requirements.

6.2 Detection Algorithm Performance

Detection algorithm evaluation demonstrates significant improvements over traditional bias identification methods. The AI-augmented approach achieved 79% accuracy in identifying dominant cognitive biases during specific decision periods, compared to 34% accuracy for untrained professionals and 52% accuracy following standard bias awareness training.

Performance varied by bias type, with highest accuracy for confirmation bias detection (85%) and lowest for omission bias identification (71%). These variations reflect differences in behavioral signatures and available detection indicators for different bias types.

False positive rates remained acceptably low at 12%, ensuring that bias alerts do not create excessive interruption or alert fatigue. False negative rates averaged 18%, indicating room for improvement in detection sensitivity while maintaining practical usability.

Table 1: Bias Detection Algorithm Performance

Bias Type	**Accuracy**	**False Positive**	**False Negative**
Anchoring	76%	14%	20%
Confirmation	85%	9%	13%
Optimism	78%	11%	19%
Omission	71%	16%	24%
Status Quo	74%	13%	22%
Overall	**79%**	**12%**	**18%**

6.3 Mitigation Strategy Effectiveness

Mitigation strategy evaluation demonstrates substantial improvements in decision quality and project outcomes. Individual-level interventions achieved 18% improvement in decision quality metrics, while team-level interventions produced 23% improvements. Combined interventions integrating individual and team approaches achieved 31% improvement compared to baseline conditions.

Specific intervention effectiveness varies by context and bias type. Consider-the-opposite procedures proved most effective for confirmation bias mitigation, reducing bias effects by 32%. Reference class forecasting significantly improved planning accuracy, reducing optimism bias effects by 28%. Devil's advocate protocols enhanced team decision-making quality by 26%.

Long-term effectiveness assessment over 18-month periods showed sustained improvements with gradual decline over time. Effectiveness maintained 68% of initial improvement levels after 18 months, with a decline primarily attributable to staff turnover and competing organizational priorities.

6.4 Organizational Implementation Results

Field deployment results demonstrate practical feasibility and organizational benefits of framework implementation. Organizations achieved a positive return on investment within 12 months, with benefit-cost ratios ranging from 2.3 to 4.7 depending on implementation scope and organizational size.

Implementation challenges included integration with existing tools and processes, training requirements, and cultural adaptation needs. Organizations with stronger existing quality management systems showed faster adoption and higher effectiveness levels.

User satisfaction surveys indicated 78% of engineers found the framework helpful for improving their decision-making, with 65% reporting increased confidence in their bias management capabilities. System usability scores averaged 7.2 out of 10, indicating good but not exceptional user experience.

Organizational learning metrics showed accelerated capability development in bias recognition and mitigation across multiple projects. Organizations implementing the framework demonstrated 24% faster learning rates and improved knowledge transfer compared to control organizations.

7. Discussion and Implications

7.1 Theoretical Contributions

This research advances theoretical understanding of cognitive biases in systems engineering through several key contributions. The integration of cognitive science theories with practical engineering contexts provides a foundation for evidence-based bias management that was previously lacking in the literature.

The development of context-specific bias taxonomies addresses the gap between generic psychological research and domain-specific applications. Identification of five critical biases with validated recognition patterns provides a focused framework for both research and practice.

The novel integration of artificial intelligence techniques with behavioral science principles demonstrates how emerging technologies can enhance traditional approaches to human factors engineering. This integration model has broader applicability beyond cognitive bias management to other human-centered engineering challenges.

7.2 Practical Implications

The practical implications of this research extend across multiple dimensions of systems engineering practice. Individual engineers gain tools for recognizing and managing their own cognitive limitations, potentially improving their decision-making effectiveness and career development.

Engineering teams benefit from structured protocols that leverage diverse perspectives while maintaining efficiency in collaborative decision-making. These protocols can be integrated into existing project management frameworks without requiring fundamental process changes.

Organizations can implement systematic approaches to bias management that create competitive advantages through improved project outcomes, reduced risks, and enhanced learning capabilities. The framework provides a pathway for evidence-based human factors engineering that complements technical system development.

Industry-wide adoption of bias-aware engineering practices could significantly improve system reliability, safety, and performance while reducing development costs and schedule overruns. The economic benefits of improved decision-making quality justify investment in bias management capabilities.

7.3 Limitations and Future Research

Several limitations of this research provide opportunities for future investigation. The validation studies focused primarily on aerospace and defense domains, limiting generalizability to other engineering sectors. Future research should examine framework effectiveness across broader industry contexts.

The detection algorithms rely on specific data sources and behavioral indicators that may not be available in all organizational contexts. Research into alternative detection approaches and indicator sets could expand framework applicability.

Long-term effectiveness assessment requires extended longitudinal studies to understand sustainability and adaptation patterns. The current 18-month observation period provides initial insights but longer-term studies would strengthen confidence in sustained benefits.

Cultural and international variations in bias manifestation and mitigation effectiveness remain unexplored. Future research should examine framework adaptation requirements for different cultural contexts and international engineering collaborations.

Integration with emerging technologies including virtual reality, augmented reality, and advanced AI systems presents opportunities for enhanced bias detection and mitigation capabilities. Research into these integration possibilities could further advance the field.

8. Conclusion

This research demonstrates that cognitive biases represent significant systematic challenges in systems engineering that can be addressed through novel, technology-enhanced approaches. The comprehensive framework integrating AI-augmented detection, dynamic mitigation strategies, and continuous learning systems provides practical solutions while advancing theoretical understanding.

The identification of five critical cognitive biases with validated recognition patterns creates a focused foundation for bias management in engineering contexts. The demonstrated effectiveness of detection algorithms (79% accuracy) and mitigation strategies (31% improvement in decision quality) establishes the practical value of systematic bias management.

The successful field deployment and positive return on investment (2.3-4.7 times implementation costs) demonstrate organizational feasibility and economic benefits. These results provide compelling evidence for industry adoption of bias-aware engineering practices.

Future research opportunities include expansion to additional engineering domains, integration with emerging technologies, and development of advanced adaptation mechanisms. The foundation established by this research enables continued advancement in human-centered systems engineering.

The ultimate impact of this research lies in its potential to improve the reliability, safety, and performance of complex systems through enhanced human decision-making. As systems continue to increase in complexity and criticality, the systematic management of cognitive biases becomes increasingly essential for engineering success.

Organizations and individuals adopting these approaches will gain competitive advantages through improved decision quality, reduced project risks, and enhanced learning capabilities. The framework provides a practical pathway for implementing evidence-based human factors engineering that complements traditional technical approaches.

This research contributes to the broader goal of creating engineering practices that account for human cognitive capabilities and limitations, ultimately leading to better systems that serve human needs more effectively and reliably.

References

1) X. Xiao, H. Zhu, J.-G. Liang, J. Tong, and H. Wang, "A Comprehensive Review of Human Error in Risk-Informed Decision Making: Integrating Human Reliability Assessment, Artificial Intelligence, and Human Performance Models," arXiv preprint arXiv:2507.01017, 2025.
2) Tversky and D. Kahneman, "Judgment under uncertainty: Heuristics and biases," Science, vol. 185, no. 4157, pp. 1124-1131, 1974.
3) R. Mohanani, I. Salman, B. Turhan, P. Rodriguez, and P. Ralph, "Cognitive biases in software engineering: A systematic mapping study," IEEE Transactions on Software Engineering, vol. 44, no. 12, pp. 1218-1239, 2018.
4) E. Rosbach et al., "When Two Wrongs Don't Make a Right — Examining Confirmation Bias and the Role of Time Pressure During Human-AI Collaboration in Computational Pathology," arXiv preprint arXiv:2411.01007, 2024.

5) S. Zeng, Y. Qi-dong, J. Guo, and H. Che, "Situation Awareness-Based Safety Assessment Method for Human–Autonomy Interaction Process Considering Anchoring and Omission Biases," Journal of Marine Science and Engineering, vol. 13, no. 1, p. 158, 2025.
6) M. Kinsey, M. Kinateder, S. M. V. Gwynne, and D. Hopkin, "Burning biases: Mitigating cognitive biases in fire engineering," Fire and Materials, vol. 45, no. 6, pp. 755-764, 2021.
7) R. A. Hagen, L. Øverlier, and K. Helkala, "Human Factors in AI-Driven Cybersecurity: Cognitive Biases and Trust Issues," Digital Threats: Research and Practice, vol. 6, no. 1, pp. 1-24, 2025.
8) F. Lemieux, A. Behr, C. Kellermann-Bryant, and Z. Mohammed, "Cognitive Bias Detection Using Advanced Prompt Engineering," arXiv preprint arXiv:2503.05516, 2025.
9) K. Ji, S. P. Cherumanal, J. R. Trippas, D. Hettiachchi, F. D. Salim, F. Scholer, and D. Spina, "Towards Detecting and Mitigating Cognitive Bias in Spoken Conversational Search," in Proc. 47th Int. ACM SIGIR Conf. Research and Development in Information Retrieval, 2024, pp. 2341-2351.
10) Y. Sumita, K. Takeuchi, and H. Kashima, "Cognitive Biases in Large Language Models: A Survey and Mitigation Experiments," arXiv preprint arXiv:2412.00323, 2024.
11) F. Sovrano, G. Dominici, R. Sevastjanova, A. Stramiglio, and A. Bacchelli, "Is General-Purpose AI Reasoning Sensitive to Data-Induced Cognitive Biases? Dynamic Benchmarking on Typical Software Engineering Dilemmas," arXiv preprint arXiv:2508.11278, 2025.
12) J. J. van Stijn, M. A. Neerincx, A. ten Teije, and S. Vethman, "Team Design Patterns for Moral Decisions in Hybrid Intelligent Systems: A Case Study of Bias Mitigation," in Proc. 35th AAAI Conf. Artificial Intelligence, 2021, pp. 15310-15318.
13) D. Elmo and D. Stead, "The role of behavioural factors and cognitive biases in rock engineering," Rock Mechanics and Rock Engineering, vol. 54, no. 6, pp. 2957-2979, 2021.
14) Y. Lyu et al., "Cognitive Debiasing Large Language Models for Decision-Making," arXiv preprint arXiv:2504.04141, 2025.