

AI-SUPPORTED MITIGATION OF COGNITIVE BIASES IN STRATEGIC DECISION SUPPORT SYSTEMS: A CONCEPTUAL MODEL¹

Stratejik Karar Destek Sistemlerinde Bilişsel Önyargıların Yapay Zekâ Destekli Sınırlandırılması: Kavramsal Bir Model

Muharrem Cihad ÖZLER¹, Tolga TEMUÇİN²

ÖZET

ABSTRACT

Bu çalışma, karmaşık karar verme ortamlarında bilişsel önyargıların belirlenmesi ve azaltılması amacıyla davranış bilimleri, yapay zekâ, stratejik karar analizi ve yöneylem araştırmasını bütünleştiren çok katmanlı kavramsal bir çerçeve önermektedir. Mevcut literatür bilişsel önyargıları, yapay zekâ temelli karar destek sistemlerini ve stratejik planlama araçlarını çoğunlukla ayrı alanlar olarak ele almakta; yanlışlık teşhisinin hiyerarşik stratejik modeller ve nicel doğrulama yöntemleriyle birlikte yapılandırıldığı bütünleşik yaklaşımlar ise sınırlı kalmaktadır. Önerilen çerçeve dört analitik katmandan oluşmaktadır: bilişsel yanlışlıkların belirlenmesi, bu yanlışlıkların Mission-Objective-Strategy-Tactics (MOST) çerçevesi içinde aşama bazlı kırılmalara eşlenmesi, TOWS matrisi aracılığıyla yapay zekâ destekli azaltım stratejilerinin geliştirilmesi ve Yöneylem Araştırması/Endüstri Mühendisliği yöntemleriyle nicel doğrulama kavramsal mimarisi. Çalışma tam ölçekli ampirik doğrulama sunmamakta; davranışsal kırılmalıkları uygulanabilir ve ölçülebilir karar destek mekanizmalarına dönüştüren kuramsal bir mimari geliştirmektedir. Doğu Akdeniz Gaz Forumu'na (EMGF) ilişkin politika odaklı bir anlatı üzerinde, sistem talimatları, rol tanımı, bağlam ve görev talimatlarından oluşan dört katmanlı prompt mimarisiyle yürütülen LLM analizi, otorite, iyimserlik ve çerçeveleme yanlışlığı sinyallerini belirlemektedir. Bu uygulama ayrıca belirlenen önyargı sinyallerinin MOST aşamalarına eşlenmesini ve TOWS-AI azaltım araçlarıyla ilişkilendirilmesini göstererek modelin operasyonel uygulanabilirliğini ve yöntemsel şeffaflığını güçlendirmektedir. Çalışma, insan yargısı, yapay zekâ destekli analiz ve OR/IE tabanlı doğrulamayı birleştirerek davranışsal operasyon yönetimi, hibrit zekâ ve stratejik karar destek literatürüne katkı sunmaktadır. **Anahtar Kelimeler:** Yapay Zekâ, Bilişsel Önyargı, Karar Destek Sistemleri, Stratejik Karar Verme, Yöneylem Araştırması

This study proposes a multi-layered conceptual framework that integrates behavioral science, artificial intelligence (AI), strategic decision analysis, and operations research to address cognitive biases in complex decision-making environments. Existing literature examines cognitive biases, AI-based decision support, and strategic planning tools separately; however, an integrated model that connects bias diagnosis with hierarchical strategic models and quantitative validation remains limited. The proposed framework is structured in four analytical layers: cognitive bias identification, mapping of phase-specific vulnerabilities within the Mission-Objective-Strategy-Tactics (MOST) framework, AI-supported mitigation through the TOWS matrix, and Operations Research/Industrial Engineering (OR/IE)-based validation conceptual architecture. The study is conceptual and integrative; it does not provide full-scale empirical validation but develops a theoretically grounded architecture that translates behavioral vulnerabilities into actionable and measurable decision-support mechanisms. An exploratory analysis using a large language model (LLM) and a four-layer prompt architecture comprising system instructions, role definition, context, and task instructions identifies authority, optimism, and framing bias signals in an EMGF policy narrative. The framework also outlines how Likert-scale bias indicators, Monte Carlo simulation, sensitivity analysis, and multi-criteria decision analysis may be used in future studies to evaluate bias reduction and decision quality improvement. By combining human judgment, AI-based analytical support, and OR/IE validation, the article contributes to behavioral operations management, hybrid intelligence, and strategic decision-support research. **Keywords:** Artificial Intelligence, Cognitive Bias, Decision Support Systems, Strategic Decision-Making, Operations Research

1. ORCID: 0009-0008-6782-4334

2. ORCID: 0000-0002-0118-9525

1. Yüksek Lisans Öğrencisi, Ankara Üniversitesi, Yapay Zeka ve Veri Mühendisliği, cihad@alumni.usc.edu

2. Öğr.El. Dr., Çankaya Üniversitesi, Endüstri Mühendisliği, tolga.temucin@gmail.com

Özler M. C. ve Temuçin T. (2026) Ai-Supported Mitigation Of Cognitive Biases In Strategic Decision Support Systems: A Conceptual Model.

Akademi Sosyal Bilimler Dergisi, C. 13, S.3, S. 218-232.

Makale Geliş Tarihi: 28 Haziran 2026 Kabul Tarihi: 3 Eylül 2026

¹ This study is an extended, revised, and journal-adapted version of the paper presented and published within the scope of DATA'26: Digital Age & Technological Advances for Sustainable Development, held in Rome, Italy, on June 03-05, 2026.



This article is licensed under a Creative Commons Attribution-Noncommercial 4.0 International license.
Bu makale Creative Commons Atıf-Gayri Ticari 4.0 Uluslararası Lisansı ile lisanslanmıştır.

GENİŞLETİLMİŞ ÖZET

Bu çalışma, stratejik karar verme süreçlerinde bilişsel önyargıların yalnızca bireysel muhakeme hataları olarak değil, örgütsel karar mimarisini biçimlendiren sistematik kırılmalıklar olarak ele alınması gerektiği varsayımından hareket etmektedir. Psikoloji, davranışsal ekonomi ve yönetim literatürü, karar vericilerin karmaşıklık ve belirsizlik altında bilgiyi her zaman rasyonel biçimde işlemediğini; çerçeveleme, teyit, aşırı güven, kayıptan kaçınma, ulaşılabilirlik, otorite ve batık maliyet gibi yanlılıkların risk algısını, seçenek değerlendirmesini ve stratejik önceliklendirmeyi etkilediğini göstermektedir. Buna karşın söz konusu bulguların stratejik planlama modelleri, yapay zekâ destekli karar destek sistemleri ve nicel doğrulama yöntemleriyle bütünleşik biçimde ele alındığı çalışmalar sınırlıdır. Bu boşluk, özellikle politika, güvenlik, enerji ve kurumsal yönetim gibi belirsizliğin yüksek olduğu alanlarda önem kazanmaktadır. Bu yönüyle çalışma, yapay zekâyı yalnızca teknik bir optimizasyon aracı olarak değil; kurumsal karar alma, yönetim, hesap verebilirlik ve politika tasarımı süreçlerini etkileyen sosyo-teknik bir unsur olarak ele almaktadır.

Çalışmada önerilen kavramsal mimari dört katmandan oluşmaktadır. İlk katman, karar süreçlerini etkileyebilecek 23 bilişsel önyargıyı tanımlamakta ve bu yanlılıkları bilişsel, duygusal ve bağlamsal etkilerine göre görünür kılmaktadır. İkinci katman, bu yanlılıkları Mission-Objective-Strategy-Tactics (MOST) çerçevesinin aşamalarına eşlemektedir. Bu çerçevede, MOST ve TOWS eşleştirmeleri sabit ve tek yönlü bir sınıflandırma olarak değil, karar ortamına, veri akışına ve stratejik önceliklere göre güncellenebilen uyarlanabilir bir yapı olarak değerlendirilmektedir. Bu sayede misyon, hedef, strateji ve taktik düzeylerinde baskın durumda olabilecek bilişsel yanlılık kümeleri bağlama duyarlı biçimde izlenebilir ve gerektiğinde yeniden sınıflandırılabilir hâle gelmektedir. Üçüncü katman, TOWS matrisini yapay zekâ destekli azaltım mekanizmalarıyla birleştirerek stratejik zayıflıkları eyleme dönük karşı önlemlere bağlamaktadır. Doğal dil işleme, duygu analizi, senaryo analizi, olasılıksal tahminleme, simülasyon ve karar panelleri bu katmanda kullanılabilecek araçlar arasında yer almaktadır. Dördüncü katman ise yöneylem araştırması ve endüstri mühendisliği yöntemlerini sürece dâhil etmektedir. Çok kriterli karar analizi, Delphi yaklaşımı, Monte Carlo simülasyonu, duyarlılık analizi, zaman serisi analitiği ve maliyet-fayda değerlendirmesi, yapay zekâ ile üretilen azaltım önerilerinin ölçülebilir biçimde sınanmasına imkân tanımaktadır. Bilişsel önyargıların seçimi, stratejik kararlarla ilişkili olma, en az bir MOST aşamasına eşlenebilme ve gözlemlenebilir bir göstergeye veya uygun bir AI/OR-IE tabanlı azaltım yöntemine sahip olma ölçütlerine dayanmaktadır. LLM analizi, sistem talimatları, rol tanımı, bağlam ve görev talimatlarından oluşan dört katmanlı prompt mimarisiyle yürütülmüştür. Model çıktıları doğrudan hüküm olarak değil, uzman değerlendirmesi gerektiren önyargı sinyalleri olarak ele alınmıştır.

Çalışma tam ölçekli ampirik doğrulama sunmamakta, bunun yerine gelecekteki uygulamalı araştırmalar için modüler ve ölçeklenebilir bir karar destek mimarisi geliştirmektedir. Doğu Akdeniz Gaz Forumu örneği, önerilen yaklaşımın politika odaklı anlatılara nasıl uygulanabileceğini göstermektedir. Dört katmanlı prompt mimarisiyle yürütülen LLM tabanlı analiz, söz konusu anlatıda otorite, iyimserlik ve çerçeveleme yanlılığı sinyallerini belirlemektedir. EMGF uygulamasında belirlenen sinyaller MOST aşamalarına eşlenmiş ve uygun TOWS-AI yanıtlarıyla ilişkilendirilmiştir. Ayrıca, nitel LLM bulgularının Likert tipi göstergelere dönüştürülmesi ve uzman puanları üzerinden ortalama önyargı değerlerinin hesaplanması önerilmiştir. Gelecek çalışmalar farklı modeller, tekrarlı koşullar, alternatif prompt yapıları ve kontrollü deneylerle çerçevenin güvenilirliğini ampirik olarak sınavabilir. Böylece çalışma, insan yargısını dışlayan değil, onu algoritmik tutarlılık ve sayısal doğrulama ile destekleyen bir hibrit zekâ yaklaşımını savunmaktadır. Sonuç olarak önerilen çerçeve; şeffaflık, hesap verebilirlik, kaynak etkinliği ve kurumsal öğrenme açısından daha dayanıklı karar destek sistemlerinin tasarımına katkı sağlayabilecek teorik bir zemin sunmaktadır.

INTRODUCTION

Strategic decision-making increasingly takes place under uncertainty, information overload, political sensitivity, and time pressure. Decision-makers rarely evaluate alternatives under perfect rationality. They use mental shortcuts that speed decisions but may distort judgment. Research shows that framing,

confirmation, overconfidence, loss aversion, anchoring, availability, status quo, and sunk cost effects can influence how organizations define problems, select evidence, set priorities, and evaluate outcomes (Acciarini et al., 2021; Berthet, 2022). These distortions may accumulate across strategic stages and become embedded in organizational routines, planning documents, performance indicators, and policy narratives.

At the same time, AI has expanded organizational analytical capacity. AI-based systems can process large volumes of structured and unstructured data, detect linguistic patterns, support scenario generation, and provide probabilistic forecasts. AI also shifts analytical tasks between humans and algorithms (Shrestha et al., 2019). Hybrid intelligence research emphasizes that robust decision systems combine human contextual understanding with algorithmic consistency, traceability, and scalability rather than replacing human judgment (Dellermann et al., 2019). This is important in strategic decision support, where political context and unclear goals cannot be solved by technical optimization alone. Accordingly, the study treats AI as part of decision-making, governance, accountability, and policy design.

Despite these advances, research on cognitive bias, AI-supported decision systems, strategic planning, and OR/IE remains fragmented. Bias studies explain irrational decisions but rarely connect them to strategic frameworks. AI studies often emphasize predictive performance. OR/IE methods provide optimization and validation without consistently modeling behavioral vulnerabilities. This article links these streams within one decision-support architecture.

The central research question is: How can cognitive biases be structurally integrated into strategic decision frameworks and mitigated through AI- and OR-based analytical approaches? The proposed framework has four layers. First, it identifies cognitive biases that may affect strategic judgment. Second, it maps these biases onto the Mission-Objective-Strategy-Tactics (MOST) framework to enable phase-specific diagnosis. Third, it uses TOWS logic to transform diagnosed vulnerabilities into AI-supported strategic responses. Fourth, OR/IE methods provide a quantitative validation layer that converts qualitative bias diagnosis into measurable indicators. The study is conceptual and does not claim full empirical validation. Its contribution lies in connecting these elements within a single sequence that moves cognitive-bias analysis from general awareness toward an operational and measurable decision-support process.

The framework also supports sustainability-oriented decision-making. AI-supported learning and evidence-based analysis relate to SDG 9.5, transparent decision architectures to SDG 16.6, and improved resource allocation under uncertainty to SDG 12.2 (United Nations Statistical Commission, 2023). Sustainability is therefore treated as a design principle for resilient organizational systems.

Table 1 summarizes the research gaps and the corresponding contributions of the four analytical layers. The table is the authors' conceptual synthesis of distinct literature streams.

Table 1: Research Gaps and Novel Contributions across Analytical Layers

No.	Analytical Layer	Research Gap	Novel Contribution
1	Cognitive bias identification	Limited connection between bias taxonomies and strategic models.	Mapping of 23 biases to strategic decision phases with AI-supported detection logic.
2	MOST framework mapping	Insufficient phase-specific integration of biases into mission, objectives, strategy, and tactics.	Identification of cognitive vulnerabilities at each MOST level.
3	TOWS strategic alignment	Weak connection between bias diagnosis and actionable strategic response.	AI-supported TOWS matrix for reframing, monitoring, scenario testing, and validation.
4	OR/IE validation	Limited quantitative assessment of behavioral mitigation outcomes.	MCDA, Monte Carlo, Delphi, sensitivity analysis, time-series analytics, and cost-benefit pathways.

1. RELATED WORK

Cognitive biases have been widely examined in psychology, behavioral economics, management, and public policy. Systematic reviews show that they influence risk perception, preference formation, information search, and evaluation under uncertainty (Acciarini et al., 2021; Berthet, 2022). Overconfidence may reduce sensitivity to uncertainty. Framing may change perceived gains and losses. Confirmation bias may narrow evidence search. Loss aversion may discourage experimentation. Strategic choices are therefore shaped not only by technical evidence but also by narratives, institutional authority, past commitments and recent events.

A key limitation is that behavioral research does not always show where bias occurs in the strategic process. Mission statements may reflect authority or optimism. Objectives may be shaped by selective evidence. Strategy formulation by availability or halo effects; and implementation by sunk cost or hindsight. MOST is used here to locate these vulnerabilities by strategic phase.

AI-supported decision-making has also developed rapidly. Organizational AI can support prediction, classification, language analysis, anomaly detection, and decision automation (Shrestha et al., 2019). In complex environments, AI can detect patterns that are difficult for human decision-makers to observe when decisions rely on large data sets or textual narratives. NLP can reveal tone, framing, and recurring assumptions in policy documents. Probabilistic models can estimate uncertainty. Dashboards can integrate performance indicators. Yet AI systems may also reproduce bias through training data, model objectives, prompt design, or human interpretation. For this reason, AI should support human judgment rather than be treated as a neutral decision-maker.

Hybrid intelligence provides the theoretical bridge between machine analysis and human responsibility. Human decision-makers contribute contextual understanding, ethical awareness, and institutional memory, while machine systems contribute consistency and computational scale (Dellermann et al., 2019). AI may flag distortions and test alternatives, but humans retain final judgment and accountability.

OR and multi-criteria decision-making methods provide another foundation. AHP, TOPSIS, VIKOR, Delphi, Monte Carlo simulation, time-series analysis, and cost-benefit evaluation support structured comparison, uncertainty modeling, and sensitivity testing (Bozkurt Uzan, 2025; Dalbudak & Rençber, 2022; Gelman et al., 2013; Linstone & Turoff, 1975). These methods improve transparency by making assumptions, weights, and trade-offs explicit. However, the methods may overlook bias in how criteria, alternatives, and preferences are defined.

OR/IE tools should therefore be embedded in a broader process that first detects and tests cognitive vulnerabilities. The proposed framework responds to this need by integrating behavioral diagnosis, MOST mapping, TOWS-based response, and quantitative validation.

2. METHODOLOGY

This study adopts a conceptual and integrative research design. It does not test hypotheses or estimate empirical effects. It synthesizes concepts from behavioral decision theory, AI decision support, strategic analysis, and OR/IE methods to construct a coherent framework. The study focuses on model development, internal consistency, and operational logic rather than statistical inference. The conceptual model draws on a structured review of literature on cognitive biases and strategic decision-making. Biases are included when they are relevant to strategic decisions, can be linked to at least one MOST phase, and have an observable indicator or a plausible AI- or OR/IE-based mitigation pathway. Biases are excluded when they lack a clear strategic link, cannot be mapped onto MOST, or have neither an observable indicator nor a plausible mitigation pathway. The final selection is therefore purposefully constructed and operationally manageable rather than exhaustive. Each retained bias is connected to MOST phases, TOWS-AI responses, and OR/IE validation tools.

The LLM component uses a four-layer prompt architecture consisting of system instructions, role definition, context, and task instructions. System instructions establish analytical rules and reliability boundaries. Role definition positions the model as a cognitive-bias analyst. Context introduces the EMGF case and the twenty-three-bias framework. Task instructions specify expected outputs, including textual evidence, justification, MOST-phase mapping, and a suitable TOWS-AI response. This structure creates a traceable path from bias identification to mitigation.

The methodology consists of four stages. The first stage identifies 23 biases selected for their recurring influence on evidence interpretation, risk evaluation, goal setting, and performance assessment (Acciarini et al., 2021; Berthet, 2022; Smith et al., 2008; The Decision Lab, 2024). The aim is to select a practical set of biases that can be mapped to strategic phases. The second stage maps these biases onto MOST, a hierarchical model connecting Mission, Objectives, Strategy, and Tactics (Business Analyst Mentor, n.d.). This enables a more precise diagnosis of where cognitive vulnerabilities arise. The third stage integrates TOWS with AI-supported mitigation mechanisms. TOWS transforms Strengths, Weaknesses, Opportunities, and Threats into strategic response categories (Visual Paradigm, n.d.; Weihrich, 1982), while AI tools support reframing, sentiment analysis, probabilistic forecasting, scenario analysis, monitoring, and consistency checks. The fourth stage introduces OR/IE validation through MCDA, Monte Carlo simulation, Delphi, sensitivity analysis, moving averages, and cost-benefit analysis (Bozkurt Uzan, 2025; Dalbudak & Rençber, 2022; Harvard Business School Online, n.d.; IBM, n.d.; Linstone & Turoff, 1975; Nau, 2023). This quantitative layer makes assumptions and trade-offs explicit without eliminating human judgment. To ensure reporting transparency, the article follows the spirit of Standards for Reporting Qualitative Research (SRQR) by clarifying the purpose, conceptual structure, analytical assumptions, limitations, and future validation pathway of the framework (O'Brien et al., 2014). Because the study is conceptual, SRQR is used only to support transparency in framework development and future evaluation.

2.1. Analytical Framework of the Study

The proposed framework can be understood as a decision-support pipeline. The framework identifies cognitive distortions, maps them to strategic levels, links them to mitigation strategies, and evaluates them quantitatively. This sequence is important because bias mitigation often remains at the level of awareness. Complex organizations instead require repeatable procedures, diagnostic categories, and measurable feedback mechanisms.

The first layer identifies bias as a structural vulnerability rather than an individual moral failure, which reduces the tendency to treat bias correction as personal criticism. The second layer maps vulnerabilities across mission, objectives, strategy, and tactics. The third layer links detected vulnerabilities to specific TOWS-AI actions such as reframing, scenario generation, or monitoring. The fourth layer uses OR/IE instruments to assess whether mitigation improves decision quality. Together, these layers create a traceable path from diagnosis to action and measurement.

The framework is modular. An organization may begin with textual bias analysis of strategic documents and later expand toward scenario simulations, MCDA, dashboards, or LLM-based narrative analysis. Another organization may start with expert workshops before adding automated tools. This modularity is necessary because data availability, analytical maturity, and institutional constraints differ across sectors. The framework therefore provides a flexible design logic rather than a rigid implementation protocol.

2.2. Bias Identification Layer

The bias identification layer focuses on mechanisms most likely to distort strategic judgment. Framing affects how problems are presented. Anchoring gives disproportionate influence to early information. Authority bias encourages excessive reliance on high-status actors. Optimism bias may lead decision-makers to overestimate favorable outcomes and underestimate constraints. Status quo and bandwagon effects support conformity, while confirmation, attentional, and overconfidence biases narrow evidence search or reduce sensitivity to uncertainty. Loss aversion and small-numbers bias may further constrain experimentation and amplify limited evidence.

At strategy and tactical levels, elimination by aspects may discard alternatives too early, while base-rate neglect may ignore relevant statistical patterns. Affect, availability, and halo effects can overvalue recent or emotionally salient successes. During implementation, cognitive dissonance, hindsight, and sunk cost may delay correction. Recency and self-serving biases may distort performance evaluation. Barnum or belief biases may give undue meaning to ambiguous feedback. Collectively, these biases influence how decision-makers define problems, justify choices, and learn from outcomes (Smith et al., 2008; The Decision Lab, 2024).

The practical value of this layer is diagnostic. It provides a vocabulary for recognizing recurring distortions in documents, meetings, dashboards, and after-action reviews. AI can scan text for signals of excessive certainty, selective evidence, authority bias, and overly optimistic framing. However, AI-based detection should be treated as a signal, not a final judgment. Human experts must assess whether a detected pattern reflects genuine bias, legitimate institutional context, or necessary strategic emphasis.

2.3. MOST Mapping Layer

MOST translates general bias categories into phase-specific strategic vulnerabilities. Mission statements define organizational purpose and identity. They are therefore particularly exposed to framing, anchoring, authority, optimism, status quo, and bandwagon effects. If the mission is framed too narrowly, later objectives and strategies may inherit that distortion. Excessive authority may suppress alternative interpretations, while optimism may cause structural constraints to be underestimated.

Objectives convert mission into measurable goals. Confirmation bias may lead organizations to select indicators that support existing assumptions; attentional bias may prioritize visible or politically salient outcomes; and overconfidence may produce unrealistic targets. Loss aversion can discourage experimentation, while reliance on small samples may create unstable goal setting. These biases matter because objectives become the measurement architecture through which later success and failure are interpreted.

Strategy formulation involves selecting broad courses of action and is vulnerable to elimination by aspects, base-rate neglect, affect, availability, and halo effects. A strategy may be preferred because it resembles recent success or seems emotionally appealing, while alternatives may be rejected too early. Tactics involve implementation and feedback and are especially vulnerable to sunk cost, cognitive dissonance, hindsight, recency, self-serving, Barnum, and belief biases. A failing initiative may continue because prior investment is hard to abandon, while unclear results may be used to defend the original decision.

Table 2 maps the selected biases onto MOST phases. The mapping is adaptive rather than fixed and may be revised according to decision context, data availability, and organizational priorities.

Table 2: Mapping of Cognitive Biases and Strategic Weaknesses within the MOST Framework

MOST Phase	Bias Source	Bias Manifestation in Phase	Strategic Weakness
Mission	Framing, Anchoring, Authority, Optimism	Mission definition is vulnerable to how the problem is framed. Leaders may anchor on initial information, defer to authority, or display over-optimism about outcomes. Leaders may define an idealistic mission by underestimating constraints and overestimating success likelihoods - a reflection of optimism bias during vision formulation.	Leadership overreliance and underestimated constraints
Mission	Status Quo, Bandwagon	Early consensus often forms around prevailing assumptions, resisting change or aligning with majority opinion.	Resistance to innovation
Objective	Confirmation, Attentional, Overconfidence	Objectives are shaped to confirm pre-existing beliefs or selective evidence, ignoring contradictory data. Overconfidence can distort measurable goal setting.	Narrow framing and ignored uncertainty
Objective	Loss Aversion, Small Numbers	Objectives may be set conservatively to avoid potential loss, or based on small data samples, reducing analytical validity.	Reduced experimentation and limited learning
Strategy	Elimination by Aspects, Base Rate	During strategy formulation, decision-makers rely on stereotypes, ignore statistical baselines, or prematurely eliminate alternatives by a single criterion.	Simplistic weighting of alternatives
Strategy	Affect, Availability, Halo	Emotional salience or recent vivid events influence which strategies appear "best." Positive impressions can be wrongly generalized (halo).	Overvaluation of recent success

Tactics	Cognitive Dissonance, Hindsight, Sunk Cost	Once implementation begins, people rationalize flawed actions (“I knew it all along”) or persist with failed tactics due to prior investment.	Resistance to corrective action
Tactics	Recency, Self-serving, Barnum, Belief	Recent experiences dominate feedback analysis; success is attributed to personal skill, failure to external causes.	Distorted performance evaluation

2.4. TOWS-AI Integration Layer

The TOWS-AI integration layer converts diagnosis into strategic response. A traditional TOWS matrix links strengths and weaknesses with opportunities and threats to guide strategic responses (Wehrich, 1982). In this framework, cognitive biases are treated as decision weaknesses that can be addressed through AI-supported analytical tools. AI is not assumed to remove bias automatically; rather, it provides alternative framings, quantitative comparisons, scenario testing, and monitoring signals that can interrupt biased routines.

For weakness-opportunity situations, AI reframing and sentiment analysis can counter framing, anchoring, authority, and attentional biases by presenting alternative interpretations of the same strategic issue. Monte Carlo simulation and Bayesian learning can counter loss aversion and small-numbers bias by displaying distributions rather than single-point expectations (Gelman et al., 2013). For strength-opportunity situations, dashboards can reduce affect, availability, and halo effects, while scenario and sensitivity analysis can challenge confirmation and overconfidence.

For weakness-threat situations, AI monitoring can identify post-decision rationalization, repeated justification of failing initiatives, and narrative patterns associated with sunk cost. Time-series analytics can reduce recency and self-serving distortions by placing recent performance within a longer trend (Nau, 2023). Consistency checks can flag selective interpretation and unsupported claims. For strength-threat situations, simulation can encourage exploration of alternative scenarios, while probabilistic forecasting and NLP-based neutrality analysis can challenge optimism, anchoring, base-rate neglect, authority-driven framing, status quo, and bandwagon effects.

Table 3 summarizes these bias-aware TOWS responses. The tools support structured challenge and monitoring rather than automated judgment.

Table 3: AI-Integrated Strategic Responses to Cognitive Biases Identified through the MOST-TOWS Framework

TOWS Quadrant	Bias Source	Strategic Weakness	AI-Based Mitigation
W-O	Framing, Anchoring, Authority, Attentional	Leadership overreliance and narrow framing	Apply AI-driven reframing models to neutralize emotional tone; use sentiment and semantic analysis tools (Bias Detection Tools) to test mission statements against cognitive bias lexicons.
W-O	Loss Aversion, Small Numbers	Risk aversion and limited experimentation	Employ Monte Carlo simulations and Bayesian learning to expand data-driven foresight; visualizing the full range of possible outcomes enables decision-makers to see uncertainty clearly, align their confidence with reality, and avoid overestimating the likelihood of success.
S-O	Affect, Availability, Halo	Overvaluation of recent success	Use AI dashboards that show both emotional trends (e.g., recent positive or negative feedback) and objective performance data together. When the emotional tone is too positive or negative, the system highlights it and reminds the user to check real numbers - helping decisions stay balanced.
S-O	Confirmation, Overconfidence	Ignored uncertainty	Create AI dashboards that let users test “what if” scenarios - for example, “what if demand drops by 10%?”. The system shows how results would change under different assumptions (a kind of Sensitivity Analysis), helping decision-makers see other

			possibilities and avoid overconfidence.
W-T	Cognitive Dissonance, Sunk Cost	Resistance to correction	Use AI-assisted review systems to monitor post-decision behavior, detect the continued investment in failing choices, and generate early alerts for corrective action.
W-T	Recency, Self-serving	Distorted performance evaluation	Use AI-based statistical analytics to monitor performance feedback over time, detect biased self-attributions, and provide balanced evaluations of success and failure.
W-T	Barnum, Belief, Hindsight	Selective interpretation	Use AI-guided feedback systems to detect vague or biased statements, flag unsupported claims, and provide logical consistency checks for more reliable evaluations.
S-T	Status Quo, Bandwagon, Optimism, Base Rate	Resistance to innovation and poor uncertainty modeling	Use AI-driven simulation tools to generate diverse perspectives, challenge groupthink, and visualize the systemic risks of conformity through scenario modelling .

2.5. OR/IE Integration and Quantitative Validation

OR/IE provides the validation engine of the framework. Cognitive-bias mitigation should be evaluated with measurable outcomes. MCDA can compare alternatives before and after AI-supported reframing. AHP can make criterion weights explicit. TOPSIS or VIKOR can show whether rankings change under different assumptions. Delphi can compare individual expert judgments with group consensus (Bozkurt Uzan, 2025; Dalbudak & Rençber, 2022; Linstone & Turoff, 1975). These methods help determine whether mitigation changes not only narratives but also the structure of the decision.

Monte Carlo simulation can replace deterministic expectations with distributions of possible outcomes, making variance, downside risk, and probability ranges explicit. This is particularly useful for optimism bias, anchoring, and loss aversion (IBM, n.d.). Sensitivity analysis can identify which assumptions drive a decision and whether conclusions are robust. Time-series tools can reduce recency effects, while cost-benefit analysis can compare the analytical cost of mitigation with the expected benefit of improved decision quality (Harvard Business School Online, n.d.).

The validation layer also supports future empirical research. Bias intensity can be measured through Likert-scale items, expert coding, textual indicators, or decision-quality metrics. Possible outcomes include consistency, robustness, transparency, stakeholder confidence, reduced error rates, and improved alignment between objectives and outcomes. The framework links qualitative diagnosis to measurement and, when needed, optimization.

Table 4: OR and IE Tools to Mitigate Cognitive Biases

No.	Relevant Bias	OR/IE Tools Supporting Bias-Aware Decision-Making	Applied Example / Practical Illustration
1	Framing Bias and Anchoring Bias	MCDA (AHP, ANP, TOPSIS)	Decision-makers anchored to the first option (e.g., “Route A is cheapest”) often overlook risk and reliability. MCDA enforces systematic weighting of multiple criteria, helping identify the option with the best cost–risk–benefit balance.
2	Authority Bias and Anchoring Bias	Delphi Method with Sensitivity Analysis	To reduce overreliance on senior experts, Delphi applies anonymous feedback rounds. Sensitivity Analysis checks how results change with different expert weightings, ensuring balanced consensus.
3	Overconfidence Bias and Optimism Bias	Monte Carlo Simulation Modeling	Overly optimistic maintenance or repair estimates distort planning. Monte Carlo simulations expose realistic variability through thousands of probabilistic outcomes.
4	Recency Bias	Exponential Smoothing and Weighted Moving	Instead of copying the latest value (forward/backward fill), weighted averages integrate recent and historical data. This smooths fluctuations and prevents overreaction to short-

		Averages	term patterns.
5	Sunk Cost Fallacy and Loss Aversion	Cost–Benefit and Decision Tree Analysis	Decision-makers may continue failing projects due to prior investment. Cost–Benefit recalculates future value independently of sunk costs, and Decision Trees visualize payoffs to support rational termination.

Several OR-based methodologies, including MCDA, Delphi with sensitivity analysis, Monte Carlo simulation, exponential smoothing, weighted moving averages, cost-benefit analysis, and decision tree analysis, can transform cognitive and behavioral bias insights into measurable, data-driven strategic formulations. As summarized in Table 4, the practical illustrations show how each method can support mitigation through quantifiable modeling practices.

3. EXPLORATORY APPLICATION: INTEGRATING LLM-BASED BIAS DETECTION WITH OR/IE QUANTITATIVE VALIDATION IN THE EMGF CASE

Although the study is primarily conceptual, this section moves beyond by applying the proposed framework to a real-world text as an illustrative case. The framework was applied to the abstract of the article entitled The East Mediterranean Gas Forum as a Platform for a Regional Energy Treaty by Klotzman and Reich (2025). The selected text discusses the anticipated institutional, legal, economic, and geopolitical contributions of a regional energy treaty within the East Mediterranean Gas Forum (EMGF).

The application is exploratory. It does not constitute full-scale empirical validation of the framework. It examines whether the proposed architecture can be operationalized through an authentic strategic narrative. It also checks whether qualitative LLM-generated bias signals can be converted into transparent quantitative indicators. The purpose is not to evaluate the political or legal performance of the EMGF or to classify the source article. The analysis identifies textual patterns which may indicate cognitive vulnerabilities requiring further expert examination.

3.1. LLM-Based Textual Analysis

The abstract was analyzed using the complete set of twenty-three cognitive biases included in the conceptual framework. The model was not restricted to the three bias categories reported in the final analysis. Instead, it evaluated the text against the full set and retained only signals supported by explicit textual evidence. To further develop and test the analytical framework, the LLM-assisted textual analysis was conducted between 3 and 6 August 2026 using OpenAI’s ChatGPT web interface, powered by GPT-5.6 Thinking with the reasoning effort set to High.

For each potential bias, the analytical procedure required identification of the relevant textual expression, a brief justification, the corresponding MOST phase, and a potential TOWS-AI mitigation response. Generated outputs were subsequently reviewed manually to exclude classifications that were unsupported, contextually weak, or excessively inferential. Following this procedure, three dominant bias signals were retained: authority bias, optimism bias, and framing bias.

Authority bias was reflected in statements that associated the EMGF’s formal status and institutional prestige with expected effectiveness. Descriptions of the EMGF as a “potent and legally binding energy organisation” and a “pre-eminent energy organisation” emphasized institutional authority, although formal status alone does not guarantee operational effectiveness.

Optimism bias appeared in forward-looking statements such as “foster energy cooperation,” “promote sustainable energy initiatives,” “stimulating economic growth,” and “ensuring energy security.” Compared with these expected benefits, the text gave less attention to political disagreements, implementation challenges, institutional limitations, and geopolitical risks.

Framing bias appeared because the text emphasized expected benefits more than possible costs, conflicts, enforcement challenges, and unintended consequences. These findings represent bias signals rather than definitive judgments about the source document. LLM-generated classifications may capture meaningful linguistic patterns, but they can also be influenced by prompt design, training-data bias, contextual

ambiguity, and false-positive pattern recognition. As Bender et al. (2021) argue through the “stochastic parrots” perspective, large language models may produce fluent and convincing text without genuinely understanding its meaning. Because fluency can be mistaken for reliability, the retained signals were treated as diagnostic indicators rather than final conclusions and were subjected to human interpretation and contextual review.

3.2. Integration with the MOST and TOWS-AI Layers

The detected bias signals were then mapped for the MOST framework. Authority bias was mainly linked to the Mission layer because the formal status of the EMGF was presented as a sign of expected effectiveness. Optimism bias was linked to both the Mission and Objectives layers because the text emphasized cooperation, economic growth, energy security, and regional stability.

Framing bias was mainly linked to the Objectives and Strategy layers. The text focused more on expected benefits than on risks, political constraints, or alternative outcomes. This may influence how objectives are defined and how strategic options are evaluated.

The abstract did not provide enough information about implementation results, performance feedback, or post-decision evaluation. Therefore, tactical biases such as sunk cost, hindsight, recency, and self-serving bias were not examined.

At the TOWS-AI stage, several responses can be used to address these bias signals. NLP-based analysis can compare positive and negative language. Scenario analysis can present favorable, neutral, and adverse outcomes. Probabilistic forecasting can make uncertainty more visible. Base-rate comparisons can also test whether expected effectiveness is based mainly on formal institutional status rather than on evidence from similar organizations.

These tools do not remove bias automatically. However, they can help decision-makers examine one-sided narratives and evaluate strategic choices more carefully.

3.3. Quantitative Assessment of Bias Indicators

To make the illustration measurable, bias indicators can be operationalized as Likert-scale items. For authority bias, an item may ask whether the perceived effectiveness of an initiative is inferred mainly from formal status. For optimism bias, an item may assess whether constraints are underrepresented relative to expected benefits. For framing bias, an item may measure whether strategic language emphasizes gains more than risks. Respondents can score each item from 1 to 5, where higher values indicate stronger bias presence. The mean score for each bias can be calculated through Equation (1). The resulting profile would show which biases are most prominent and where mitigation should be prioritized.

In practical application, the LLM findings would first be converted into survey items based on the textual evidence identified in the source document. For example, the expressions “potent and legally binding energy organisation” and “pre-eminent energy organisation” would support the item developed for authority bias. Statements emphasizing cooperation, economic growth, energy security, and regional stability would support the optimism-bias item. Similarly, the greater emphasis on expected benefits than on political risks, implementation costs, and alternative outcomes would support the framing-bias item. Domain experts or organizational decision-makers could then evaluate these items using the same five-point Likert scale. This process provides a clear link between qualitative LLM-based detection and quantitative expert assessment.

A simple numerical example illustrates this transition. Suppose five experts assign authority-bias scores of 4, 4, 3, 4, and 5. Using Equation (1), the mean authority-bias score would be 4.0. If optimism bias and framing bias receive mean scores of 4.6 and 3.8, respectively, optimism bias would be identified as the highest-priority area for mitigation. The TOWS-AI layer could then prioritize scenario analysis and probabilistic forecasting for optimism bias, neutrality analysis for framing bias, and base-rate comparison for authority bias. These numerical values are provided only to demonstrate the calculation process and do not represent empirical findings of the present study.

The purpose of this case illustration is therefore methodological. It shows how a strategic narrative can move through the four layers of the framework: LLM-supported bias detection, MOST phase mapping, TOWS-AI response design, and OR/IE-based measurement. The illustration also clarifies the boundary of the study. The article does not claim that the EMGF is empirically biased in a definitive sense. It demonstrates how an analyst could structure a bias-aware decision-support process for similar policy narratives.

Equation 1. Mean Bias Intensity Score

$$\text{BiasMean}_i = \frac{1}{n} \sum_{j=1}^n x_{ij} \quad (1)$$

Source: Author's own elaboration. In the equation, x_{ij} denotes the score assigned by participant j to bias i , and n denotes the total number of participants.

3.4. Prompt Design and Future Research

Prompt engineering should be treated as a central methodological component of LLM-based bias detection rather than as a simple user input. Recent research has identified more than 200 prompting techniques, demonstrating both the rapid development of the field and the growing need for standardized prompt structures (Schulhoff et al., 2025). Prompts shape model behavior, define the analytical context, and determine the expected form and scope of the output. In this sense, they function as structured instructions that can adapt, extend, or limit the capabilities of an LLM (White et al., 2023).

Future applications of the proposed framework may use a layered prompt architecture consisting of four components: system instructions, role definition, context, and task instructions. System instructions establish the general behavioral rules, analytical boundaries, and reliability requirements of the model, such as relying only on explicit textual evidence and avoiding unsupported inferences. Role definition specifies the expertise and analytical perspective assigned to the model, such as a cognitive-bias analyst or strategic decision-support expert. Context provides the case-specific background, source text, conceptual framework, bias taxonomy, and limits of the analysis. Task instructions define the exact operations to be performed, including identifying bias signals, presenting supporting evidence, mapping each signal onto the relevant MOST phase, recommending a TOWS-AI response, and following a predefined output format and classification criteria.

In the present analysis, this four-part structure was applied directly. The system instructions required the model to rely only on explicit textual evidence and avoid unsupported classifications. The role definition assigned the model the perspective of a cognitive-bias analyst and strategic decision-support expert. The context introduced the EMGF abstract, the MOST-TOWS framework, and predefined set of twenty-three cognitive biases. The task instructions required the model to identify potential bias signals. The model also provided the relevant textual evidence and a brief justification. Each signal was then mapped onto the appropriate MOST phase. Finally, the model recommended a suitable TOWS-AI response. In simplified form, the model was instructed to analyze the EMGF text against the twenty-three-bias framework, retain only text-supported signals, and report the bias type, supporting expression, justification, MOST phase, and TOWS-AI mitigation response.

Future studies should also compare different foundation models, domain-specific fine-tuned models, and repeated model runs using the same text and coding framework. Testing alternative prompt structures would help determine whether identified bias signals are stable or mainly depend on a particular model or wording.

For greater transparency and reproducibility, future studies should report the complete prompt, model name and version, access date, reasoning configuration, and available generation settings. Accordingly, prompt engineering should be considered not only a technical step but also a critical research-design element that

directly affects the quality, consistency, and reliability of LLM-based analysis (Schulhoff et al., 2025; White et al., 2023).

4. DISCUSSION

The proposed framework contributes to decision-support research by connecting behavioral diagnosis with strategic architecture and quantitative validation. Its first contribution is conceptual integration. Rather than treating cognitive bias, AI, and OR/IE as separate domains, the framework places them in a sequential relationship. Bias identification clarifies what may go wrong in judgment. MOST mapping clarifies where it may go wrong in the strategic process. TOWS-AI integration clarifies how mitigation can be designed. OR/IE validation clarifies how mitigation can be measured. This sequence helps prevent the common problem of discussing cognitive bias in abstract terms without embedding it in operational decision routines.

The second contribution is the phase-specific treatment of bias. Strategic decisions are layered. A distorted mission can affect objectives. Biased objectives can shape strategy. A flawed strategy can constrain tactics. Tactical feedback can then reinforce the original narrative through hindsight, self-serving, or sunk cost effects. By mapping biases to MOST phases, the framework encourages decision-makers to diagnose vulnerabilities before they cascade. This is especially relevant in domains where early framing decisions are difficult to reverse, such as public policy, defense planning, energy governance, and large-scale organizational transformation.

The third contribution concerns the role of AI. The framework does not treat AI as a replacement for human judgment. Such a claim would be inconsistent with both behavioral decision research and hybrid intelligence theory. Instead, AI is positioned as a structured analytical partner. It can detect textual patterns, generate alternative framings, test assumptions, and support monitoring. Yet it must be governed by human interpretation, domain expertise, and accountability. This balanced view is important because AI systems may themselves be biased through training data, prompt design, model objectives, and user interpretation. Bias-aware AI decision support therefore requires governance, documentation, and critical review. The proposed framework therefore follows a human-in-the-loop approach. The LLM identifies potential bias signals, but human experts review the textual evidence, assess the context, and confirm or reject the model's classifications. Final interpretation and decision responsibility remain with human decision-makers rather than the AI system.

The fourth contribution is the emphasis on measurable validation. Many bias mitigation efforts depend on training, checklists, or expert intuition. These approaches may be useful but difficult to evaluate. OR/IE methods provide a way to test whether mitigation changes criteria weights, scenario robustness, risk perception, or decision consistency. For example, MCDA can reveal whether alternative rankings change after reframing. Monte Carlo simulation can show whether decision-makers become more aware of downside risk. Sensitivity analysis can identify whether a strategy depends on fragile assumptions. These tools make bias mitigation more measurable and transparent. The framework also has practical implications. Organizations can use it to review strategic documents, policy narratives, project portfolios, risk registers, and after-action reports. A pilot implementation could begin with a small set of biases and one decision phase, such as identifying framing and confirmation bias in objective setting. Over time, the process could expand to dashboards, simulations, expert panels, and performance evaluation. The modular structure makes the framework suitable for organizations with different levels of analytical maturity.

5. LIMITATIONS AND FUTURE RESEARCH

The main limitation of the study is the absence of full-scale empirical validation. The framework is theoretically grounded and structurally coherent, but it has not yet been tested in controlled experiments, field studies, or longitudinal organizational applications. Therefore, the article does not claim measurable bias reduction or decision-quality improvement. It identifies how such outcomes could be measured in future research. This limitation is deliberate because the purpose of the article is framework development rather than empirical estimation.

A second limitation concerns the use of LLM-based bias detection. LLMs can identify linguistic patterns and generate plausible interpretations, but their outputs depend on prompts, model architecture, training data, and evaluation criteria. They may over-detect bias, miss context, or produce confident but contestable judgments. Therefore, LLM outputs should be validated through expert review, expert agreement and comparison with baseline methods. Future studies should test whether LLM-supported bias detection improves consistency compared with human-only analysis.

A third limitation is its application across different contexts. The framework is designed to be applicable across domains, but specific bias patterns and mitigation tools will vary by context. Energy policy, defense planning, finance, healthcare, and corporate strategy involve different data structures, accountability mechanisms, and risk tolerances. Future research should therefore apply the framework in multiple domains and compare which biases are most common at each MOST phase.

Future empirical studies can develop Likert-scale instruments for the 23 biases identified in the framework. They can test pre- and post-mitigation bias scores, compare decision quality before and after AI-supported reframing, and evaluate whether MCDA or Monte Carlo outputs alter expert judgments. Longitudinal studies can examine whether repeated use of the framework improves organizational learning. Experimental studies can compare human-only, AI-only, and hybrid intelligence decision processes. Such research would help determine when AI-supported bias mitigation is most useful and where human oversight remains indispensable.

CONCLUSION

This study proposes an integrated analytical framework for AI-driven cognitive bias mitigation in strategic decision support systems. By linking cognitive bias identification to the MOST framework, the TOWS matrix, AI-supported mitigation tools, and OR/IE validation methods, the article offers a structured way to move from behavioral diagnosis to measurable decision improvement. The framework demonstrates that bias mitigation should not be treated as a general awareness exercise. It should be embedded in the architecture of strategic planning, decision support, and quantitative evaluation. The exploratory EMGF application further demonstrates how this analytical sequence can be applied to a real policy-oriented text.

The article's main contribution lies in its integrative logic. It brings together behavioral science, hybrid intelligence, strategic analysis, and operations research in a modular model. The EMGF illustration shows how the framework can be applied to policy-oriented narratives, identifying authority, optimism, and framing bias signals while outlining a pathway for measurement through Likert-scale indicators and quantitative validation. More specifically, the LLM-based analysis identified authority bias, optimism bias, and framing bias as the three dominant bias signals in the selected text. Authority bias was mainly linked to the Mission layer. Optimism bias was associated with the Mission and Objectives layers, while framing bias was connected to the Objectives and Strategy layers. These signals were linked to suitable TOWS-AI responses, including neutrality analysis, scenario analysis, probabilistic forecasting, and base-rate comparison.

The application also demonstrates how qualitative LLM findings can be connected to quantitative assessment. Text-based bias signals can be converted into Likert-scale items and evaluated by domain experts or organizational decision-makers. Mean bias scores can then indicate which biases require greater attention and which mitigation tools should be prioritized. The numerical example presented in the study illustrates this transition but does not represent empirical findings obtained from actual participants.

The framework is not a finished empirical instrument but a design blueprint for future applied research. Accordingly, the findings should be interpreted as evidence of operational feasibility rather than full empirical validation. The study does not claim that the EMGF or the source article is definitively biased. Instead, it demonstrates that potential bias signals can be identified, mapped, reviewed through human interpretation, and linked to measurable decision-support actions. LLM outputs are therefore treated as diagnostic indicators rather than final judgments because they may be influenced by prompt design, training-data bias, contextual ambiguity, and false-positive pattern recognition.

Strategic decision-making will continue to face uncertainty, contested evidence, and institutional pressure. Under such conditions, cognitive biases cannot be fully eliminated. They can, however, be made visible, mapped, challenged, and measured. AI can support this process when it is combined with human expertise and OR/IE validation. Future studies can test the framework through expert surveys, controlled experiments, repeated LLM runs, different foundation models, domain-specific fine-tuned models, and alternative prompt structures. These studies can evaluate whether the framework improves consistency, transparency, robustness, and decision quality. The proposed framework therefore argues for a hybrid, transparent, and evidence-aware approach to strategic decision support, one in which human judgment is not replaced but strengthened through a human-in-the-loop oversight and structured analytical safeguards.

REFERENCES

- Acciarini, C., Brunetta, F., & Boccardelli, P. (2021). Cognitive biases and decision-making strategies in times of change: A systematic literature review. *Management Decision*, 59(3), 638-658. <https://doi.org/10.1108/MD-07-2019-1006>
- Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610-623). Association for Computing Machinery. <https://doi.org/10.1145/3442188.3445922>
- Berthet, V. (2022). The impact of cognitive biases on professionals' decision-making: A review of four occupational areas. *Frontiers in Psychology*, 12, Article 802439. <https://doi.org/10.3389/fpsyg.2021.802439>
- Bozkurt Uzan, Ş. (2025). Facilitating decision-making processes in packaging and graphic media: A review of MCDM methods from 2008 to 2024. *Sakarya University Journal of Computer and Information Sciences*, 8(2), 286-300.
- Business Analyst Mentor. (n.d.). MOST analysis - What it is and how to use it. <https://businessanalystmentor.com/most-analysis/>
- Dalbudak, E., & Rençber, Ö. F. (2022). Çok kriterli karar verme yöntemleri üzerine literatür incelemesi. *Gaziantep Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 4(1), 1-17. <https://doi.org/10.55769/gauniibf.1068692>
- Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering*, 61(5), 637-643. <https://doi.org/10.1007/s12599-019-00595-2>
- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). *Bayesian data analysis* (3rd ed.). CRC Press.
- Harvard Business School Online. (n.d.). What is cost-benefit analysis and how to use it for decision-making. <https://online.hbs.edu/blog/post/cost-benefit-analysis>
- IBM. (n.d.). Monte Carlo simulation. <https://www.ibm.com/think/topics/monte-carlo-simulation>
- Klotsman, I., & Reich, A. (2025). The East Mediterranean Gas Forum as a platform for a regional energy treaty. *Israel Law Review*, 58(1), 86-123. <https://doi.org/10.1017/S0021223724000177>
- Koenig-Workman, I. (2024). Decision tree analysis. The Decision Lab. <https://thedecisionlab.com/reference-guide/statistics/decision-tree-analysis>
- Linstone, H. A., & Turoff, M. (Eds.). (1975). *The Delphi method: Techniques and applications*. Addison-Wesley.
- Medi-ASD. (2026). International Conference on Data Science and Applications (DATA'26): Conference scope and topics. <https://data.medi-asd.org/>

- Nau, R. (2023). Moving averages. Duke University. <https://people.duke.edu/~rnau/411avg.htm>
- O'Brien, B. C., Harris, I. B., Beckman, T. J., Reed, D. A., & Cook, D. A. (2014). Standards for reporting qualitative research: A synthesis of recommendations. *Academic Medicine*, 89(9), 1245-1251. <https://doi.org/10.1097/ACM.0000000000000388>
- Schulhoff, S., Ilie, M., Balepur, N., Kahadze, K., Liu, A., Si, C., Li, Y., Gupta, A., Han, H., Schulhoff, S., Dulepet, P. S., Vidyadhara, S., Ki, D., Agrawal, S., Pham, C., Kroiz, G., Li, F., Tao, H., Srivastava, A., ... Resnik, P. (2025). *The prompt report: A systematic survey of prompt engineering techniques* [Preprint]. arXiv. <https://doi.org/10.48550/arXiv.2406.06608>
- Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 61(4), 66–83. <https://doi.org/10.1177/0008125619862257>
- Smith, E. D., Piattelli-Palmarini, M., & Bahill, A. T. (2008). Cognitive biases affect the acceptance of tradeoff studies. In *Decision modeling and behavior in complex and uncertain environments* (pp. 227-249). Springer. https://doi.org/10.1007/978-0-387-77131-1_10
- The Decision Lab. (2024). List of cognitive biases. <https://thedecisionlab.com/biases>
- United Nations Statistical Commission. (2023). Global indicator framework for the Sustainable Development Goals and targets of the 2030 Agenda for Sustainable Development (A/RES/71/313). <https://unstats.un.org/sdgs/indicators/indicators-list/>
- Visual Paradigm. (n.d.). TOWS analysis: A comprehensive guide. <https://online.visual-paradigm.com/knowledge/strategic-analysis/tows-analysis-guide/>
- Weihrich, H. (1982). The TOWS matrix-A tool for situational analysis. *Long Range Planning*, 15(2), 54-66. [https://doi.org/10.1016/0024-6301\(82\)90120-0](https://doi.org/10.1016/0024-6301(82)90120-0)
- White, J., Fu, Q., Hays, S., Sandborn, M., Olea, C., Gilbert, H., Elnashar, A., Spencer-Smith, J., & Schmidt, D. C. (2023). *A prompt pattern catalog to enhance prompt engineering with ChatGPT* [Preprint]. arXiv. <https://doi.org/10.48550/arXiv.2302.11382>

AUTHORS' CONTRIBUTION LEVELS: First Author 80%, Second Author 20%.
ETHICS COMMITTEE APPROVAL: Ethics committee approval was not required for this study.
FINANCIAL SUPPORT: This study received no financial support.
CONFLICT OF INTEREST: The authors declare that there is no potential conflict of interest.