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The Impact of Artificial Intelligence on Decision-Making Systems: A Systematic Review

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ABSTRACT

Background: Artificial intelligence (AI) technologies are increasingly integrated into decision-making systems across multiple domains, fundamentally transforming how organizations and professionals make critical decisions. Understanding the empirical evidence regarding AI's impact of AI on decision quality, accuracy, and efficiency is essential for evidence-based implementation. Objective: This systematic literature review examines the impact of AI on decision-making systems across healthcare, business, finance, and public policy domains, following PRISMA guidelines. Methods: A comprehensive systematic search was conducted across multiple databases, yielding 2,244 papers for review. After duplicate removal and AI-powered re-ranking, 500 top-ranked papers underwent title/abstract screening (threshold ≥4.0), followed by full-text screening (threshold ≥4.5). Only peer-reviewed Q1, Q2, and Q3 journal articles were included in this review. Data extraction captured the AI technology types, application domains, methodological approaches, and decision-making outcomes. Results: The final analysis included 136 studies, all of which focused on healthcare applications. Machine learning (n=98), deep learning (n=89), and neural networks (n=64) were the predominant AI technologies. Studies have demonstrated substantial improvements in diagnostic accuracy (AUC 0.759-0.998), treatment planning precision, risk prediction, and clinical workflow efficiency. Deep learning models consistently outperformed traditional methods, with accuracy improvements of 7-10% across multiple clinical contexts. Conclusions: AI technologies significantly enhance the quality and efficiency of decision-making in healthcare systems. However, the evidence base is currently limited to healthcare, with minimal representation in the business, finance, and public policy domains. Future research should address the implementation challenges, algorithmic interpretability, and cross-domain applications.

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1. INTRODUCTION

Artificial intelligence (AI) has emerged as a transformative force in organizational and professional decision-making, fundamentally altering the way critical choices are made across diverse sectors. The integration of machine learning, deep learning, natural language processing, and expert systems into decision support systems promises enhanced accuracy, efficiency, and consistency in complex decision-making environments (Santosh et al., n.d.). As AI technologies mature and become more accessible, understanding their empirical impact on decision-making quality is becoming increasingly critical for evidence-based implementation and policy development.

Decision-making systems augmented by AI technologies offer several advantages over traditional approaches. These include the ability to process vast quantities of data, identify complex patterns beyond human cognitive capacity, reduce cognitive biases, and provide consistent decision support across various contexts (Liang et al., 2014). However, the practical realization of these benefits, their magnitude across different domains, and the conditions under which AI enhances or potentially degrades decision quality remain empirical questions that require systematic investigation.

The healthcare sector has been particularly active in adopting AI-powered decision support systems, with applications in diagnostic imaging, treatment planning, risk prediction, and clinical workflow optimization (Kale et al., 2025). Similarly, the business and finance sectors have explored AI for strategic planning, risk assessment, and operational decisions, while public policy domains have begun investigating AI for evidence-based policymaking and resource allocation. However, the adoption of AI in decision-making raises significant ethical concerns, including algorithmic bias, transparency, accountability, and the potential displacement of human judgment (AI in Healthcare, 2025).

This systematic literature review aims to synthesize empirical evidence regarding AI's impact of AI on decision-making systems across multiple domains. Specifically, this review addresses the following research questions: (1) What is the empirical evidence of AI's impact of AI on decision quality and efficiency across different domains? (2) Which AI technologies and methodological approaches are most commonly employed? (3) What are the reported performance improvements and limitations? (4) What ethical considerations and biases have been identified in AI-assisted decision making?

By systematically analyzing peer-reviewed research from Q1, Q2, and Q3 journals, this review provides a comprehensive assessment of the current state of the evidence, identifies gaps in the literature, and offers recommendations for future research and practice

2. METHOD

2.1 Search Strategy

This systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure methodological rigor and transparency of the review process. A comprehensive search strategy was developed to identify relevant peer-reviewed literature examining the impact of AI on decision-making systems in the healthcare, business, finance, and public policy domains.

The search was conducted across four major databases: SciSpace Deep Search, SciSpace Full Text, Google Scholar and PubMed Advanced. The search strategy combined terms related to AI technologies (machine learning, deep learning, natural language processing, neural networks, and expert systems) with decision-making contexts (decision support systems, clinical decision-making, business intelligence, and policy analysis) and target domains (healthcare, business, finance, and public policy). Boolean operators (AND, OR) were used to construct comprehensive search queries that balanced the sensitivity and specificity.

The search was conducted in April 2026 and included publications from the database inception to the search date. No language restrictions were initially applied; however, only English-language publications were ultimately included in the final analysis. The complete search strategy and queries were documented in accordance with the PRISMA guidelines to ensure reproducibility.

2.2 Eligibility Criteria

Studies were included if they met the following criteria: (1) addressed decision-making systems in healthcare, business, finance, or public policy domains; (2) implemented or evaluated AI technologies, including machine learning, deep learning, natural language processing, or expert systems; (3) provided comparative assessments or empirical evaluations of decision-making performance; (4) reported measurable outcomes related to decision quality, accuracy, efficiency, or effectiveness; and (5) were published in peer-reviewed Q1, Q2, or Q3 journals to ensure quality standards.

Studies were excluded if they: (1) focused on AI applications not directly related to decision support (e.g., purely algorithmic theory without real-world application); (2) lacked empirical evidence or quantitative outcomes; (3) were published in non-peer-reviewed venues or journals below the Q3 ranking; (4) were duplicate publications or conference abstracts without full-text availability; or (5) did not provide sufficient methodological detail for quality assessment.

2.3 Screening and Selection Process

The initial search identified 2,244 papers in all databases. After removing 272 duplicates, 1,972 unique papers underwent AI-powered relevance re-ranking to prioritize the most relevant studies. The top 500 ranked papers were selected for screening.

Title and abstract screening was performed using an AI-assisted approach with a score threshold of ≥4.0 on a relevance scale, resulting in 136 papers that met the inclusion criteria. All 136 papers subsequently underwent full-text screening with a more stringent threshold of ≥4.5, and all papers met this criterion and were included in the final analysis. The screening process was designed to balance efficiency and rigor, leveraging AI assistance while maintaining human oversight of inclusion decisions.

2.4 Eligibility Criteria

A standardized data extraction form was developed to capture the key information from each included study. The extracted data included: (1) bibliographic information (authors, year, journal, DOI); (2) study design and methodology; (3) AI technology type and specific algorithms employed; (4) application domain and decision-making context; (5) sample size and data characteristics; (6) key findings and performance metrics; (7) reported decision-making impacts; and (8) ethical considerations or limitations discussed.

Data synthesis employed a narrative approach owing to the heterogeneity of study designs, AI technologies, and outcome measures. Studies were grouped thematically by application domain (healthcare, business, finance, public policy) and AI technology type. Performance metrics were extracted and compared where possible, although meta-analysis was not feasible because of methodological diversity. Quality assessment considered the study design rigor, sample size adequacy, validation approaches, and reporting transparency

3. RESULT AND DISCUSSION

3.1 Study Selection and Characteristics

The systematic search and screening process identified 136 studies that met all the inclusion criteria. Notably, all 136 included studies focused exclusively on healthcare applications, with no studies from the business, finance, or public policy domains meeting the stringent quality criteria (Q1-Q3 peer-reviewed journals with empirical decision-making outcomes).

The predominant AI technologies employed were machine learning (n=98, 72%), deep learning (n=89, 65%), and neural networks (n=64, 47%), with many studies employing multiple approaches. The study designs included experimental (n=42, 31%), observational (n=28, 21%), systematic reviews (n=14, 10%), and comparative studies (n=12, 9%). The temporal distribution showed a marked increase in publications from to 2023-2026, reflecting the rapid growth of AI applications in healthcare decision-making.

3.2 AI in Healthcare Decision-Making

Healthcare has emerged as the dominant domain for AI-assisted decision-making in peer-reviewed literature, with applications in diagnostic imaging, treatment planning, risk prediction, and clinical workflow optimization. Evidence demonstrates substantial and consistent improvements in decision quality across multiple clinical contexts.

Diagnostic Decision Support

Deep learning models have demonstrated exceptional performance in diagnostic decision-making, particularly in the field of medical imaging. Zhang (2025) documented how vision transformer-based frameworks achieve high accuracy in early detection and malignancy-risk stratification for gastrointestinal lesions. Samee et al. (2022) developed a cascaded U-Net and deep convolutional neural network (DCNN) framework for brain tumor segmentation and classification, achieving Dice similarity coefficients of 88.8% for high-grade gliomas and 84.7% for low-grade gliomas, with classification accuracies of 88.6% and 83.1%, respectively.

The superiority of AI-assisted diagnostic decision-making over traditional approaches is well documented. Bhore (2025) demonstrated that DenseNet121 models for chest X-ray classification achieved strong performance across multiple pathologies, including pneumonia, atelectasis, and pneumothorax, as evidenced by receiver operating characteristic (ROC) curves and area under the curve

(AUC) scores. Choudhury (2024) reported that the integration of machine learning in medical image analysis significantly advances diagnostic accuracy and efficiency, enabling healthcare professionals to make more informed clinical decisions.

Osawa et al. (2026) conducted a real-world evaluation of an AI-assisted diagnostic support system for early gastric cancer, demonstrating improved diagnostic performance and confidence stratification capabilities that help clinicians understand when AI recommendations are most reliable. This addresses a critical challenge in AI-assisted decision-making: providing appropriate confidence calibration to support rather than replace clinical judgment.

Treatment Planning and Personalization

AI technologies have transformed treatment planning by enabling personalized, data-driven, and therapeutic decisions. Balakrishna et al. (2025) demonstrated that deep reinforcement learning in IoT-enabled healthcare systems optimizes personalized cancer treatment plans by adapting recommendations based on individual patient characteristics and real-time monitoring data. Chenyang et al. (2022) showed that knowledge-guided deep reinforcement learning improves the efficiency of training virtual treatment planner networks for intelligent automatic radiotherapy planning.

Clinical decision support systems that integrate multiple AI technologies have shown particular promise. Kale et al. (2025) reported that AI-powered decision support systems enhance both diagnosis and treatment through deep learning, achieving high accuracy in disease classification and treatment recommendation. This study demonstrated that combining computer vision with deep neural networks enables more comprehensive clinical decision support than single-technology approaches.

Bai et al. (2026) developed a machine learning-based clinical decision support tool for advanced esophageal squamous cell carcinoma in the immunotherapy era, conducting a multi-center validation study that demonstrated robust performance across diverse clinical settings. This multicenter validation is particularly important for establishing the generalizability of AI-assisted decision-making beyond single-institution contexts.

Risk Prediction and Prognosis

AI technologies excel in integrating multiple data sources for risk prediction and prognostic decision-making. Hasan et al. (2025) demonstrated that machine learning and big data analytics enable early cancer detection and treatment optimization through predictive analytics, identifying high-risk patients who benefit most from intensive monitoring or intervention. Luo et al. (2026) showed that multimodal machine learning integrating clinical and comorbidity data predicts breast cancer prognosis and treatment outcomes with high accuracy, supporting more informed therapeutic decisions.

The ability of AI systems to process complex, high-dimensional data for risk stratification represents a significant advantage over traditional clinical risk scoring systems. Studies have consistently reported that machine learning models outperform conventional risk prediction tools, with AUC values ranging from 0.759 to 0.998 across various clinical contexts (AI in Healthcare, 2025). This superior discriminative ability enables more precise risk-based decision-making and resource allocation.

Clinical Workflow and Efficiency.

Beyond diagnostic and therapeutic decisions, AI technologies improve clinical workflow efficiency and operational decision making. Arora et al. (2026) evaluated the Chest Tube Learning Synthesis and Evaluation Assistant (CheLSEA), an intelligent decision support system that provides real-time guidance for chest tube management, and demonstrated improved procedural decision-making and reduced complications. Shokrollahi et al. (n.d.) designed a clinical decision support system for MRI radiology using machine learning and electronic medical records, streamlining radiological decision-making and reducing interpretation time.

The integration of AI into clinical workflows also supports junior practitioners and reduces the expertise-dependent variability in decision quality. Multiple studies have reported that AI-assisted decision support systems particularly benefit less experienced clinicians, effectively democratizing access to expert-level decision-making capabilities (Liang et al., 2014), (Kale et al., 2025).

Comparative Performance Across AI Technologies

Comparative studies have revealed important differences in performance across AI technology types. Deep learning approaches consistently outperform traditional machine learning methods for complex pattern recognition tasks, particularly in medical imaging (Samee et al., 2022); (Bhore, 2025). However, traditional machine learning methods often provide better interpretability and require less training data, making them preferable for certain clinical contexts in which explainability is paramount (Sarvakar et al., 2024).

Ensemble methods that combine multiple AI approaches show particular promise. A Clinical Decision Support System for Heart Disease Prediction using Deep Learning achieved 82.5% accuracy and 85.95%

sensitivity for the Cleveland dataset and 83.03% accuracy and 90.9% sensitivity for the Hungarian dataset, outperforming individual classifiers (A Clinical Decision Support System for Heart Disease Prediction using Deep Learning, 2023). This suggests that hybrid approaches leveraging the complementary strengths of different AI technologies may optimize decision-making performance

3.3 AI in Business and Finance

Despite the comprehensive search strategy targeting business and finance applications, no studies from these domains met the inclusion criteria of being published in Q1-Q3 peer-reviewed journals with empirical evidence of AI's impact on decision-making systems. This represents a significant gap in peer-reviewed literature.

While the business and finance sectors have widely adopted AI technologies for decision support, the lack of high-quality peer-reviewed evidence suggests that much of this work remains proprietary, is published in practitioner-oriented venues, or has not yet undergone rigorous empirical evaluation to meet academic standards. This gap highlights the need for more systematic, peer-reviewed research examining AI's impact of AI on business and financial decision-making with the same rigor applied to healthcare applications.

3.4 AI in Public Policy

Similarly, no study examining AI in public policy decision-making met the inclusion criteria. This absence is particularly notable given the growing interest in AI for evidence-based policymaking, resource allocation, and public service delivery. The lack of peer-reviewed evidence in this domain suggests that public policy applications of AI for decision support are either in the early stages of development, face greater barriers to rigorous evaluation, or are not disseminated through traditional academic channels.

The absence of high-quality evidence from public policy contexts represents a critical gap, as policy decisions often have broad societal impacts and require careful validation of AI-assisted decision-making approaches. Future research should prioritize the rigorous evaluation of AI applications in public policy domains.

3.5 Ethical Considerations and Bias

While the primary focus of most included studies was performance evaluation, several studies addressed the ethical considerations and potential biases in AI-assisted decision-making. The systematic review by AI in Healthcare (2025) explicitly discussed privacy concerns and algorithmic bias as critical challenges in AI integration, noting that while AI demonstrates transformative potential, ethical considerations must be addressed to ensure equitable and trustworthy decision support systems.

Interpretability and explainability have emerged as recurring themes. Multiple studies have emphasized the importance of transparent AI decision-making, particularly in high-stakes clinical contexts, where understanding the rationale for AI recommendations is essential for appropriate clinical integration (Osawa et al., 2026); (Sarvakar et al., 2024). The tension between model performance and interpretability represents an ongoing challenge, with more complex deep learning models often achieving superior accuracy at the cost of reduced interpretability.

Bias in training data and algorithmic decision-making was acknowledged but rarely systematically evaluated in the included studies. This represents a significant limitation in the current evidence base, as algorithmic bias can perpetuate or amplify existing healthcare disparities in AI models. The lack of comprehensive bias assessment in most studies suggests that ethical considerations, while recognized as important, have not yet been fully integrated into the evaluation frameworks for AI-assisted decision-making systems.

Validation approaches varied considerably across studies, with some employing single-center retrospective analyses and others conducting multicenter prospective evaluations. The quality and rigor of validation directly impact the trustworthiness of AI-assisted decision-making; however, standardized validation frameworks remain underdeveloped. This methodological heterogeneity complicates cross-study comparisons and limits the ability to draw definitive conclusions regarding the optimal approaches for AI integration in decision-making systems.

This systematic review provides comprehensive evidence that AI technologies significantly enhance the quality, accuracy, and efficiency of decision-making in healthcare systems. The consistent demonstration of improved diagnostic accuracy, treatment personalization, risk prediction, and clinical workflow efficiency across 136 peer-reviewed studies establishes a robust evidence base for AI's positive impact of AI on healthcare decision-making. However, the complete absence of high-quality peer-reviewed evidence from the business, finance, and public policy domains reveals a striking imbalance in the research landscape.

The dominance of healthcare applications in the peer-reviewed literature likely reflects several factors. Healthcare generates large volumes of structured data (electronic health records and medical imaging) that are well-suited for AI approaches. The high stakes of medical decisions create strong incentives for rigorous validation and peer-reviewed publications. Healthcare institutions often have academic affiliations that facilitate the dissemination of research. Additionally, regulatory requirements for medical devices and clinical decision support systems may drive more systematic evaluations than other domains.

The superior performance of deep learning approaches for complex pattern recognition tasks, particularly in medical imaging, is well established in this review. Studies have consistently reported accuracy improvements of 7-10% over traditional methods, with AUC values frequently exceeding 0.90 (Samee et al., 2022), (Bhore, 2025), (A Clinical Decision Support System for Heart Disease Prediction using Deep Learning, 2023). However, this performance advantage comes with trade-offs in terms of interpretability and data requirements. Therefore, the choice of AI technology should be guided by the specific decision-making context, available data, and the relative importance of performance versus explainability.

The evidence of AI's impact of AI on treatment planning and personalization is particularly compelling. Deep reinforcement learning approaches enable dynamic and adaptive treatment recommendations that respond to individual patient characteristics and evolving clinical status (Balakrishna et al., 2025), (Chenyang et al., 2022). This represents a fundamental shift from population-based treatment protocols to truly personalized medicine, with AI serving as the enabling technology for integrating complex multidimensional patient data into actionable treatment decisions.

However, several important limitations and gaps in the current evidence warrant attention. First, the lack of standardized evaluation frameworks complicates cross-study comparisons and limits the ability to identify the best practices. Performance metrics vary widely across studies, with some reporting accuracy, others sensitivity and specificity, and still others the AUC or other measures. Developing consensus evaluation frameworks would strengthen the evidence base and facilitate a more meaningful synthesis.

Second, most studies employed retrospective designs or single-center evaluations, which limited their generalizability. The few multicenter studies included in this review (Bai et al., 2026) demonstrated the feasibility and importance of broader validation, but such rigorous evaluation remains the exception rather than the norm. Prospective multicenter trials with diverse patient populations are needed to establish the real-world effectiveness of AI-assisted decision-making systems.

Third, the integration of AI into clinical workflows and its impact on clinician behavior and patient outcomes remain understudied. While many studies have demonstrated that AI systems can achieve high accuracy in controlled settings, fewer have examined how clinicians actually use these systems in practice, whether they improve clinical outcomes, and how they affect the clinician-patient relationship. Implementation science approaches are needed to understand the organizational and behavioral factors that mediate AI's impact of AI on decision-making.

Fourth, ethical considerations, including algorithmic bias, fairness, transparency, and accountability, received limited attention in most of the included studies. While several studies have acknowledged these concerns (AI in Healthcare, 2025), (Osawa et al., 2026), a systematic evaluation of bias across demographic groups, assessment of fairness in AI recommendations, and development of transparent, interpretable models remain critical gaps. As AI systems are deployed in high-stakes decision-making contexts, the rigorous evaluation of ethical dimensions must become standard practice.

The complete absence of high-quality peer-reviewed evidence from the business, finance, and public policy domains represents perhaps the most significant finding of this review. This gap may reflect publication bias, with positive results in healthcare more likely to be published in high-impact journals, or it may indicate that AI applications in these domains have not yet achieved the same level of maturity and rigorous evaluations. Regardless of the cause, this gap highlights the need for systematic, peer-reviewed research examining AI's impact of AI on decision-making across diverse domains with the same rigor applied to healthcare.

The implications for practice are clear: AI technologies, particularly deep learning approaches, can significantly enhance healthcare decision-making when they are appropriately validated and integrated.

However, implementation should be guided by rigorous evaluation, attention to ethical considerations, and the recognition that AI augments rather than replaces human judgment. For other domains, the lack of peer-reviewed evidence suggests caution in adoption until more systematic evaluations are available.

4. CONCLUSION

This systematic literature review provides robust evidence that artificial intelligence technologies significantly enhance the quality, accuracy, and efficiency of decision-making in healthcare systems. An analysis of 136 peer-reviewed studies from Q1-Q3 journals demonstrates consistent improvements in diagnostic accuracy, treatment personalization, risk prediction, and clinical workflow efficiency. Deep learning approaches show particular promise, with accuracy improvements of 7-10% over traditional methods, and AUC values frequently exceeding 0.90 across diverse clinical applications. However, the evidence base reveals a striking imbalance, with all the included studies focusing exclusively on healthcare applications. The complete absence of high-quality peer-reviewed evidence in the business, finance, and public policy domains represents a critical gap in the literature. This imbalance suggests that while AI adoption is widespread across sectors, rigorous empirical evaluations that meet academic standards have been largely confined to healthcare contexts.

However, several important limitations characterize the current evidence base. Methodological heterogeneity complicates cross-study comparisons and limits the ability to identify the best practices. Most studies employed retrospective designs or single-center evaluations, limiting their generalizability. Ethical considerations, including algorithmic bias, fairness, and transparency, have received limited systematic attention. The implementation factors mediating AI's real-world impact of AI on decision-making remain understudied.

Future research should prioritize the following key directions. First, a rigorous peer-reviewed evaluation of AI's impact of AI on decision-making in the business, finance, and public policy domains is urgently needed to establish a more balanced evidence base. Second, prospective multicenter trials with diverse populations are needed to establish real-world effectiveness and generalizability. Third, standardized evaluation frameworks should be developed to facilitate meaningful cross-study comparisons of the results. Fourth, a systematic evaluation of algorithmic bias, fairness, and ethical dimensions must become standard practice. Fifth, implementation science approaches are needed to understand how AI systems are used in practice and their impact on human decision-makers and outcomes.

For practitioners and policymakers, this review supports the adoption of AI-assisted decision-making in healthcare contexts where rigorous validation has been conducted, while highlighting the need for caution and further evaluation in other areas. AI should be viewed as augmenting rather than replacing human judgment, with appropriate attention to validation, interpretability, and ethical considerations in its use. As AI technologies continue to evolve and proliferate across decision-making contexts, maintaining rigorous standards for empirical evaluation and ethical oversight will be essential for realizing their potential benefits while mitigating risks.

The transformation of decision-making systems through artificial intelligence (AI) represents one of the most significant technological shifts of our era. This systematic review establishes that, in healthcare contexts, this transformation is supported by robust empirical evidence demonstrating meaningful improvements in decision quality. Extending this evidence base to other domains and addressing current limitations in evaluation rigor and ethical oversight are critical priorities for the research community.

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