# Systematic Review of Artificial Intelligence Applications in Decision Support Systems

**Mustafa Abdulhadi Ben Hmaida**

The Higher Institute of Science and Technology – Misrata, Libya

bofa.benhmaida@gmail.com

**Article information**

**Key words**

*Artificial Intelligence - Machine Learning - Decision Support Systems*

*Received 18 05 2026, Accepted 10 06 2026, Available online 11 06 2026*

**Abstract**

Artificial Intelligence (AI) has become a key enabler of modern Decision Support Systems (DSS), enhancing decision-making processes across healthcare, business, finance, industry, cybersecurity, education, and smart cities. This systematic review synthesizes evidence from 23 studies published between 2023 and 2026 to examine the applications, benefits, challenges, and future directions of AI-driven DSS. The findings reveal that AI technologies, including machine learning, deep learning, expert systems, predictive analytics, and explainable AI, significantly improve decision accuracy, operational efficiency, resource optimization, and predictive capabilities. Healthcare emerged as the most prominent application domain, where AI supports diagnosis, prognosis, treatment planning, and clinical workflow management. Business and financial sectors utilize AI for strategic planning, forecasting, and supply chain optimization, while industrial applications focus on predictive maintenance and risk assessment. Despite these advantages, challenges such as data quality issues, privacy concerns, algorithmic transparency, ethical considerations, and regulatory limitations continue to affect implementation. The review also highlights a growing shift toward Human-Centered AI, emphasizing collaboration between intelligent systems and human experts. Overall, AI demonstrates substantial potential to strengthen DSS performance when supported by transparent algorithms, reliable data infrastructures, and effective governance frameworks.



bofa.benhmaida@gmail.com

## I. Introduction

Artificial Intelligence (AI) has fundamentally transformed the design and functionality of modern Decision Support Systems (DSS), enabling organizations to move beyond static data analysis toward intelligent, adaptive, and predictive decision-making environments. Traditional decision support platforms were primarily developed to assist users by organizing information and generating analytical reports based on predefined rules. Contemporary AI-driven systems operate differently. They continuously learn from historical observations, identify nonlinear relationships within massive datasets, estimate future outcomes, and recommend actions that evolve as new information becomes available [1].

The growing availability of digital information has accelerated this transformation across virtually every economic sector. Healthcare institutions generate millions of patient records, medical images, laboratory results, and clinical reports every year. Financial organizations process enormous streams of transactional data in real time. Industrial enterprises collect sensor measurements from interconnected production systems, while governments increasingly rely on digital infrastructures for planning and policy evaluation. Under these conditions, manual analysis becomes insufficient for timely decision-making, creating an environment where AI-enhanced DSS provide measurable operational value [2].

Healthcare has emerged as one of the most extensively investigated domains for AI-supported decision-making. Recent systematic evidence demonstrates that intelligent Clinical Decision Support Systems (CDSS) contribute to diagnostic assistance, prognosis estimation, treatment planning, organizational resource allocation, shared physician–patient decision-making, and patient self-management. These systems transform heterogeneous medical information into structured recommendations through predictive algorithms and knowledge-based reasoning mechanisms, allowing clinicians to make faster and more consistent decisions while preserving professional judgment [1].

Rapid methodological advances have further expanded the capabilities of AI-powered CDSS. Machine learning algorithms, deep neural networks, expert systems, and ensemble prediction models are increasingly integrated into clinical workflows to improve disease detection and optimize therapeutic interventions. Comprehensive systematic reviews covering more than a decade of research indicate that AI technologies can support nearly every stage of healthcare decision-making when appropriately implemented and clinically validated [2].

Interpretability has become another defining characteristic of modern AI applications. Although complex deep learning architectures often achieve superior predictive performance, many healthcare professionals remain hesitant to trust recommendations produced by opaque computational models. Research examining explainable clinical decision support distinguishes transparent “ante-hoc” approaches from post-processing explanation techniques designed for black-box systems. Such developments seek to preserve predictive accuracy while making algorithmic reasoning understandable to human users, thereby strengthening trust and facilitating safe deployment [3].

Outside healthcare, strategic business management has experienced substantial benefits from intelligent decision support technologies. AI-driven analytical platforms combine forecasting algorithms, optimization techniques, and data mining procedures to improve demand prediction, customer segmentation, marketing effectiveness, and resource allocation. Rather than merely presenting descriptive statistics, these systems convert operational data into actionable strategic recommendations that support executive planning under uncertain market conditions [4].

The integration of AI has also influenced financial management and supply chain operations. Intelligent financial decision support frameworks employ big data analytics and autonomous reasoning mechanisms to optimize financing strategies, shorten cash-conversion cycles, evaluate operational risks, and coordinate multi-tier supply networks. Predictive algorithms continuously monitor financial indicators and generate recommendations that enable organizations to respond proactively instead of reacting after disruptions have already occurred [5].

Industrial environments illustrate another important direction of AI-enabled DSS evolution. Predictive maintenance systems analyze sensor streams collected from manufacturing equipment and technical infrastructure to estimate component degradation before failures occur. Such architectures replace conventional schedule-based maintenance with condition-based interventions supported by machine learning models capable of detecting subtle operational anomalies that human observers may overlook [6].

Sustainable development initiatives have similarly benefited from AI-assisted decision support. Smart city infrastructures increasingly integrate Internet of Things (IoT) technologies with recurrent neural networks and predictive optimization algorithms to forecast electricity demand, improve energy distribution, reduce carbon emissions, and support environmentally sustainable planning. Decision support therefore extends beyond organizational management into broader societal applications where computational intelligence contributes directly to public policy implementation [7].

Educational institutions have recently begun incorporating AI-driven DSS to improve academic planning and administrative governance. Empirical investigations reveal that successful implementation depends primarily on organizational readiness and high-quality institutional data rather than algorithmic sophistication alone. Consequently, technological advancement must be accompanied by appropriate governance structures, infrastructure investment, and digital transformation strategies to realize meaningful improvements in decision quality [8].

Despite these advances, widespread adoption remains constrained by several technical and organizational challenges. Data privacy concerns, fragmented information sources, regulatory uncertainty, algorithmic bias, limited transparency, and ethical accountability continue to influence implementation outcomes across sectors. Reviews synthesizing evidence from multiple industries consistently identify explainability and governance as essential prerequisites for sustainable AI deployment, particularly when automated recommendations influence high-impact decisions involving human welfare or financial risk [3], [9].

Another prominent research trend emphasizes human-centered artificial intelligence rather than autonomous replacement of professional expertise. Modern DSS architectures increasingly position AI as an augmentation mechanism that assists experts by generating evidence-based recommendations while preserving final human authority. Human-centered frameworks incorporate transparent interfaces, interactive explanations, and collaborative reasoning processes designed to strengthen user confidence without diminishing professional responsibility [10].

Recent systematic investigations suggest that this collaborative paradigm may represent the future direction of intelligent decision support. Instead of maximizing automation alone, researchers increasingly focus on balancing computational performance with interpretability, fairness, usability, and ethical accountability. Such considerations are particularly important in medicine, public administration, and critical infrastructure, where decisions carry significant legal and societal consequences [10].

Although the volume of research concerning AI applications in Decision Support Systems has expanded rapidly during the past decade, existing evidence remains dispersed across specialized domains and heterogeneous methodological traditions. Many reviews concentrate exclusively on healthcare, strategic management, cybersecurity, or industrial automation, limiting opportunities to identify broader interdisciplinary trends. A comprehensive synthesis integrating findings across multiple sectors is therefore necessary to understand how AI technologies reshape decision-making processes in contemporary organizations.

Accordingly, this systematic review aims to consolidate current evidence regarding Artificial Intelligence applications in Decision Support Systems, examine dominant implementation domains, identify the principal computational approaches employed in recent research, evaluate reported benefits and persistent challenges, and highlight emerging directions that may guide future academic investigation and practical system development.

## II. Methodology

This study employed a systematic literature review methodology to synthesize contemporary evidence concerning Artificial Intelligence applications in Decision Support Systems. The review was designed to provide a structured and comprehensive assessment of current research while identifying recurring implementation patterns, technological trends, methodological characteristics, and unresolved challenges across multiple application domains.

Unlike narrative reviews that rely primarily on subjective interpretation, systematic reviews follow predefined procedures for evidence identification, selection, extraction, and synthesis. This methodological framework improves transparency and reduces selection bias by ensuring that included studies satisfy explicit relevance criteria before contributing to the final analysis.

The evidence base used in this review consisted exclusively of the scholarly studies provided in the reference collection accompanying this work. Each document was treated as an independent source regardless of publication type or application domain. The dataset includes systematic reviews, scoping reviews, bibliometric analyses, empirical investigations, conceptual frameworks, prototype implementations, simulation studies, and case-based analyses published between 2023 and 2026. Together, these publications provide extensive coverage of AI-supported decision-making across healthcare, business management, finance, cybersecurity, higher education, industrial systems, smart cities, and technical risk assessment.

The review process was conducted through four consecutive stages. During the identification phase, all available publications addressing AI-enabled decision support technologies were collected from the supplied reference corpus. Subsequently, titles, abstracts, and reported objectives were examined to determine thematic relevance. Studies focusing primarily on artificial intelligence applications without meaningful decision support components were excluded from further consideration. Publications directly investigating AI-assisted decision-making mechanisms, intelligent recommendation systems, or clinical decision support architectures were retained for qualitative synthesis.

Following study selection, a standardized extraction framework was developed to improve analytical consistency. Information recorded from each publication included publication year, principal objective, application domain, research methodology, AI techniques employed, decision support functions, implementation outcomes, reported benefits, and documented limitations. This structured extraction process facilitated systematic comparison despite differences in research design and disciplinary context.

The diversity of included studies made quantitative meta-analysis inappropriate. Considerable heterogeneity exists regarding computational techniques, evaluation metrics, implementation environments, sample sizes, and reported performance indicators. Some investigations analyze prototype systems through simulation experiments, whereas others synthesize hundreds of published studies or evaluate organizational implementation through observational methods. Pooling numerical results across such heterogeneous evidence could produce misleading conclusions. Consequently, qualitative thematic synthesis was selected as the primary analytical strategy.

Repeated examination of the extracted information enabled the identification of several recurring thematic categories. These include healthcare and clinical decision support systems, strategic organizational management, financial intelligence and supply chain optimization, industrial predictive maintenance, cybersecurity applications, sustainable energy management within smart cities, educational administration, explainable artificial intelligence, human-centered system design, and ethical or regulatory considerations. Individual studies were classified according to their dominant contribution while acknowledging that many simultaneously addressed multiple thematic dimensions.

Particular attention was devoted to identifying the computational mechanisms through which AI improves decision support capabilities. Across the reviewed literature, recurrent technologies include supervised machine learning, deep neural networks, expert systems, fuzzy inference models, predictive analytics, cognitive computing platforms, explainable AI algorithms, recurrent neural networks, rule-based reasoning engines, and hybrid architectures combining symbolic knowledge with data-driven learning. Instead of merely cataloguing these technologies, the review examines how they generate operational value by transforming raw information into evidence-based recommendations suitable for real-world decision environments.

Methodological quality was further strengthened by the substantial representation of systematic reviews employing internationally recognized reporting standards. Several healthcare-focused investigations explicitly adopted PRISMA guidelines and synthesized evidence from major scientific databases before formulating conclusions regarding AI implementation effectiveness [2], [10]. Other studies complemented this evidence through structural equation modeling, simulation frameworks, bibliometric mapping, prototype validation, and practical organizational case studies, thereby expanding methodological diversity while reinforcing the robustness of recurring findings [4], [5], [8].

The synthesis strategy prioritized conceptual integration over numerical aggregation. Similar findings reported independently across different sectors were interpreted as indicators of broader technological patterns rather than isolated observations. For example, issues surrounding transparency, trust, data quality, and organizational readiness consistently emerged across healthcare, education, finance, and strategic management, suggesting that these challenges represent cross-disciplinary characteristics of AI-enabled decision support rather than domain-specific limitations.

Finally, references throughout this review are presented according to the IEEE citation system. Each source receives a numerical identifier corresponding to its first appearance within the text, and subsequent citations retain the same identifier to ensure consistency across all sections of the manuscript. This approach provides a coherent foundation for the Results and Discussion sections that follow and facilitates clear linkage between synthesized findings and their supporting evidence.

## III. Results

The qualitative synthesis of the included literature demonstrates that Artificial Intelligence has evolved from a supplementary computational technology into a fundamental component of contemporary Decision Support Systems (DSS). Despite differences in application domains, methodological approaches, and computational architectures, the reviewed studies consistently indicate that AI enhances analytical capacity, accelerates evidence generation, and improves the quality of complex decision-making processes.

A notable observation emerging from the collected evidence is the overwhelming concentration of research within the healthcare sector. Several systematic reviews identify clinical decision support as the dominant field for AI implementation, reflecting the increasing demand for intelligent systems capable of processing large volumes of heterogeneous medical information while supporting clinicians in diagnosis, prognosis, and treatment planning [1], [2]. Human-centered AI frameworks further reinforce this trend by proposing architectural models that integrate computational intelligence with physician supervision rather than replacing human expertise entirely [10].

### A. AI Applications in Healthcare Decision Support Systems

Healthcare constitutes the most mature application area represented in the reviewed studies. AI-based Clinical Decision Support Systems (CDSS) are employed across multiple stages of patient care, including disease detection, diagnostic interpretation, therapeutic planning, outcome prediction, hospital resource allocation, and patient self-management.

Several systematic reviews demonstrate that machine learning algorithms significantly improve diagnostic performance when compared with traditional analytical approaches. Predictive models trained on electronic health records and medical imaging datasets can identify clinically relevant patterns that assist physicians in making more informed decisions while reducing diagnostic variability [1], [2].

Interpretability represents a recurring requirement within healthcare implementations. Rather than relying exclusively on black-box algorithms, researchers increasingly advocate explainable AI mechanisms capable of presenting understandable reasoning pathways to clinicians. Transparent prediction models improve user confidence, facilitate regulatory compliance, and reduce barriers to clinical adoption [3].

Disease-specific implementations further illustrate the diversity of AI-supported healthcare applications. Cardiovascular medicine employs intelligent systems for risk assessment, screening, disease management, and treatment optimization through predictive analytics integrated with clinical workflows [11]. Oncology applications similarly demonstrate substantial agreement between AI-generated treatment recommendations and multidisciplinary expert panels, suggesting that intelligent DSS can function effectively as evidence-based second-opinion tools in complex therapeutic environments [12].

Emergency medicine has also benefited from mobile AI technologies designed for rapid stroke identification and prehospital triage. Smartphone-based applications supported by deep learning algorithms improve early detection capabilities and accelerate communication between emergency responders and specialized treatment centers, particularly in geographically dispersed regions [13], [14].

Recent investigations addressing musculoskeletal disorders report similarly encouraging outcomes. Machine learning models applied to chronic low back pain management achieve high predictive performance in identifying surgical candidates and estimating recovery trajectories, thereby reducing subjective variability in conventional clinical assessment procedures [15].

Prototype implementations combining Random Forest algorithms with SHAP explainability techniques demonstrate that interpretable predictive frameworks can simultaneously achieve high diagnostic accuracy while preserving clinician trust and facilitating practical integration into healthcare workflows [16].

### B. Strategic Business and Organizational Decision Support

Outside healthcare, AI-driven DSS have become increasingly important for strategic planning and organizational management. Contemporary business environments generate continuous streams of operational, financial, and market information that exceed human analytical capacity. AI technologies address this challenge by extracting hidden relationships from structured and unstructured datasets before converting these patterns into actionable recommendations.

Case-based investigations reveal that AI-supported decision platforms improve demand forecasting, marketing campaign effectiveness, and strategic resource allocation through integrated data-intelligence-action frameworks [4]. Instead of merely producing descriptive reports, these systems automate analytical reasoning processes and continuously refine predictions as additional operational information becomes available.

High-level strategic reviews similarly conclude that neural networks, expert systems, and genetic algorithms substantially strengthen organizational intelligence by supporting scenario evaluation, market analysis, and financial planning while reducing decision costs associated with routine administrative activities [17].

Reviews focusing on management and information technology further indicate that AI enables data-driven governance through predictive analytics and machine learning techniques capable of improving resource optimization across organizational structures. Nevertheless, researchers consistently identify a gap between technological sophistication and managerial interpretation skills, emphasizing the continuing importance of human expertise during strategic decision-making [18].

Small business consulting provides another emerging application area. Hybrid intelligent decision support systems integrating rule-based reasoning with machine learning preserve inference transparency while simultaneously exploiting data-driven predictive capabilities. Such architectures appear particularly suitable for organizations operating with limited historical datasets and constrained analytical resources [19].

### C. Financial Decision Support and Supply Chain Optimization

Financial decision support has undergone rapid transformation through the incorporation of AI technologies and big data analytics. Intelligent financial platforms continuously monitor transactional information, evaluate operational risks, estimate financing requirements, and optimize resource allocation across interconnected economic networks.

Simulation-based investigations involving real-world supply chain finance implementations report substantial reductions in cash conversion cycles and financing costs following AI integration. Autonomous reasoning mechanisms improve liquidity management while strengthening resilience against operational uncertainty through predictive analysis and continuous optimization [5].

The reviewed evidence therefore suggests that AI extends beyond forecasting individual financial indicators and increasingly functions as an integrated strategic advisor capable of coordinating complex multi-tier supply ecosystems under dynamic market conditions.

### D. Smart Cities and Sustainable Energy Management

Artificial Intelligence has also become an important component of decision support infrastructures designed for sustainable urban development. Smart city platforms combine Internet of Things technologies with predictive algorithms to monitor energy consumption, estimate future demand, and optimize resource distribution across interconnected infrastructure networks.

Research investigating AI-driven energy management highlights recurrent neural networks and intelligent forecasting mechanisms as effective tools for balancing electricity demand while reducing carbon emissions. Rather than applying static scheduling strategies, these systems continuously adapt operational recommendations based on evolving environmental conditions and historical consumption patterns [7].

The reviewed literature therefore positions AI-enabled DSS as a significant contributor to sustainability objectives by integrating predictive modeling with real-time infrastructure management.

### E. Industrial Systems and Predictive Maintenance

Industrial applications emphasize proactive operational management through predictive maintenance and intelligent monitoring technologies. Sensor-equipped production environments continuously generate large quantities of performance information that machine learning algorithms analyze to estimate equipment degradation before catastrophic failures occur.

Research addressing technical system risk assessment demonstrates that intelligent prediction models improve maintenance scheduling, reduce infrastructure downtime, and support efficient resource allocation through continuous evaluation of environmental and operational variables [6].

Bibliometric investigations additionally reveal rapid expansion of AI and cognitive computing research within industrial decision support, particularly regarding predictive maintenance, logistics optimization, and integrated production management. Data collection and integration emerge as foundational requirements for successful industrial AI implementation, reinforcing the importance of high-quality information infrastructures [20].

### F. Cybersecurity and Technical Risk Management

Cybersecurity represents another rapidly developing application domain for AI-enabled decision support. Machine learning algorithms assist analysts by identifying malicious activities, classifying cyber threats, detecting phishing attacks, and recognizing abnormal behavioral patterns across complex digital environments.

Large-scale reviews examining hundreds of cybersecurity publications conclude that algorithm selection should depend on the characteristics of specific attack categories rather than adopting universal prediction models. AI therefore functions as an adaptive analytical layer capable of supporting human experts through rapid pattern recognition and automated threat prioritization [21].

Defense-oriented applications further demonstrate the flexibility of AI-assisted decision support. Physics-based simulations combined with generative adversarial networks enable intelligent systems to recommend strategic response scenarios during high-risk operational environments, improving situational awareness and supporting complex tactical decision-making processes [22].

### G. Educational Decision Support Systems

Educational institutions increasingly adopt AI technologies to improve institutional governance and administrative planning. Structural equation modeling studies indicate that successful AI-DSS implementation depends primarily on organizational readiness and data quality rather than system complexity itself.

Empirical evidence suggests that robust information infrastructures and institutional preparedness exert significantly greater influence on implementation success than algorithmic sophistication, highlighting the organizational dimension of intelligent decision support adoption [8].

### H. Human-Centered AI, Trust, and Explainability

One of the strongest themes emerging across the reviewed literature concerns the importance of explainability and human-centered design. Multiple systematic reviews conclude that technical performance alone is insufficient for successful deployment if users cannot understand or trust algorithmic recommendations.

Healthcare professionals consistently identify transparency, reliability, usability, and collaborative interaction as essential determinants of trust in AI-supported clinical systems [9]. Human-centered architectures therefore prioritize physician oversight, interactive explanations, and decision augmentation rather than complete automation [10].

Recent evaluations of AI-empowered CDSS similarly report that perceived usefulness and operational efficiency facilitate adoption, whereas opaque black-box outputs remain significant psychological barriers preventing wider implementation [23].

### I. Cross-Domain Trends

Despite disciplinary differences, several common patterns emerge across the synthesized evidence.

First, predictive analytics represents the dominant computational capability underlying modern AI-enabled DSS regardless of application sector. Second, explainability and transparency repeatedly appear as prerequisites for sustainable adoption, especially in high-risk environments involving human safety or financial responsibility. Third, data quality consistently exerts greater influence on system effectiveness than algorithmic complexity alone. Finally, the literature increasingly supports collaborative intelligence models in which AI enhances rather than replaces expert judgment.

Collectively, these findings demonstrate that Artificial Intelligence is reshaping Decision Support Systems by integrating advanced computational learning with human expertise, thereby enabling more adaptive, evidence-driven, and context-aware decision-making across healthcare, business management, finance, industry, cybersecurity, education, and sustainable development.

## IV. Discussion

The findings synthesized in this systematic review demonstrate that Artificial Intelligence has become a transformative component of modern Decision Support Systems rather than merely an auxiliary computational tool. Across healthcare, business management, finance, industrial engineering, cybersecurity, and education, AI technologies consistently improve the speed of information processing and expand the analytical capabilities available to human decision-makers. However, the reviewed evidence also indicates that successful implementation depends on organizational readiness, data quality, transparency, and human oversight as much as algorithmic sophistication.

Unlike earlier generations of DSS that relied primarily on predefined logical rules and static databases, AI-enabled systems continuously adapt to changing environments through machine learning, predictive modeling, and automated knowledge extraction. This adaptive capability allows organizations to shift from retrospective reporting toward proactive decision-making based on anticipated future events rather than historical observations alone [1], [2].

The concentration of publications in healthcare is particularly noteworthy. More than any other domain, medicine has embraced AI-driven decision support to improve diagnosis, prognosis estimation, treatment planning, and operational resource management. The reviewed literature consistently demonstrates that intelligent Clinical Decision Support Systems enhance physician performance without eliminating the importance of professional expertise. Instead, AI functions as an analytical partner capable of processing extensive medical information while leaving final responsibility to clinicians [2], [3], [10].

Another important observation concerns explainability. Although deep learning models frequently achieve exceptional predictive accuracy, opaque computational reasoning remains one of the principal barriers limiting practical adoption. Multiple systematic reviews emphasize that healthcare professionals are considerably more willing to integrate AI recommendations into clinical practice when explanations accompany predictions. Consequently, explainable AI should not be regarded merely as a technical enhancement but rather as a fundamental requirement for trustworthy decision support systems [3], [9], [23].

Business-oriented investigations reveal similar patterns. Organizations increasingly employ AI-powered DSS for demand forecasting, market analysis, financial planning, and strategic resource allocation. Yet implementation success appears to depend less on algorithmic complexity than on the organization's ability to integrate high-quality data into coherent decision-making workflows. AI generates value only when reliable information supports predictive inference [4], [17], [18].

Financial applications reinforce this conclusion. Intelligent supply chain decision support systems successfully reduce financing costs and optimize liquidity management through predictive analytics and autonomous reasoning mechanisms. Nevertheless, these benefits emerge only when continuous access to integrated transactional datasets enables accurate model updating and risk estimation [5].

Industrial environments provide additional evidence that AI is reshaping operational management through predictive maintenance strategies. Traditional maintenance schedules typically rely on predefined service intervals regardless of actual equipment condition. AI-driven DSS replace this approach with condition-based monitoring that estimates component degradation from sensor observations and recommends maintenance interventions before failures occur. Such systems simultaneously reduce operational downtime and improve resource utilization [6], [20].

The reviewed cybersecurity literature further illustrates AI's ability to support complex decision environments characterized by rapidly evolving threats. Machine learning algorithms continuously classify abnormal behavior, detect malicious activity, and prioritize security responses. However, algorithm selection remains context dependent because different cyberattack categories require different analytical approaches. Universal prediction frameworks appear less effective than specialized adaptive models optimized for specific operational scenarios [21], [22].

An equally important finding concerns the increasing emphasis on Human-Centered Artificial Intelligence (HCAI). Earlier visions of AI frequently promoted complete automation of decision-making processes. Contemporary research instead advocates collaborative architectures in which computational intelligence augments human reasoning while preserving expert supervision and ethical accountability. Such frameworks recognize that many real-world decisions involve contextual knowledge, social considerations, and moral judgment that remain difficult to encode algorithmically [10].

Table 1. Summary of Major AI Application Domains in Decision Support Systems

| Application Domain | Primary AI Functions | Reported Benefits | Representative References |
|---|---|---|---|
| Healthcare | Diagnosis, prognosis, treatment planning | Improved clinical accuracy and personalized care | [1], [2], [3], [11] |
| Business Management | Demand forecasting, strategic planning | Better resource allocation and market intelligence | [4], [17], [18] |
| Supply Chain & Finance | Risk prediction, cash-flow optimization | Reduced financing costs and improved efficiency | [5] |
| Smart Cities | Energy forecasting and optimization | Lower carbon emissions and sustainable planning | [7] |
| Industrial Systems | Predictive maintenance | Reduced downtime and proactive maintenance | [6], [20] |
| Cybersecurity | Threat detection and attack classification | Faster response and improved situational awareness | [21], [22] |
| Education | Institutional planning | Enhanced administrative decision-making | [8] |

Table 2. Common Challenges Reported Across Reviewed Studies

| Challenge | Impact on DSS Performance | Studies Reporting the Issue |
|---|---|---|
| Lack of explainability | Reduced user trust | [3], [9], [23] |
| Poor data quality | Lower prediction accuracy | [8], [18] |
| Privacy and ethical concerns | Delayed implementation | [9] |
| Organizational readiness | Influences deployment success | [8] |
| Black-box algorithms | Limited clinician acceptance | [3], [23] |
| Regulatory uncertainty | Slows adoption | [9] |

The synthesis also highlights that improvements in predictive accuracy alone do not guarantee successful implementation. Data governance repeatedly emerges as a decisive factor affecting system reliability. Educational institutions implementing AI-DSS demonstrate that organizational readiness and information quality exert greater influence than computational complexity, suggesting that infrastructure investment should precede large-scale AI deployment [8].

Interestingly, several independent studies converge on the same conceptual direction despite addressing entirely different sectors. Healthcare researchers advocate explainable AI to strengthen physician trust; business scholars emphasize transparent strategic analytics; industrial investigations require interpretable predictive maintenance recommendations; and cybersecurity researchers recommend adaptive but accountable machine learning systems. These converging findings indicate that transparency constitutes a universal design principle rather than a domain-specific requirement.

Another cross-disciplinary observation concerns the transition from reactive to predictive management. Conventional DSS generally summarize historical events, whereas AI-enhanced systems estimate future developments before they occur. Forecasting disease progression, predicting equipment failures, anticipating financing requirements, and identifying cybersecurity threats all reflect this broader shift toward anticipatory decision-making supported by computational intelligence.

Despite the positive evidence, the literature reveals several unresolved limitations. Most empirical investigations evaluate AI within controlled institutional settings or prototype implementations rather than large multinational operational environments. Generalizability therefore remains uncertain for organizations with limited digital infrastructure or inconsistent data collection procedures. Moreover, ethical concerns surrounding privacy, fairness, algorithmic bias, and accountability continue to require multidisciplinary solutions involving policymakers, engineers, and domain experts simultaneously.

The reviewed studies collectively support the conclusion that Artificial Intelligence substantially enhances Decision Support Systems when integrated with high-quality data, transparent reasoning mechanisms, and active human supervision. Future progress is therefore likely to depend less on developing increasingly complex algorithms and more on designing trustworthy socio-technical ecosystems that combine computational intelligence with responsible organizational governance.

## V. Conclusion

Artificial Intelligence has rapidly evolved into a foundational technology for modern Decision Support Systems (DSS), fundamentally changing how organizations collect information, analyze complex datasets, and formulate evidence-based decisions. The studies synthesized in this systematic review collectively demonstrate that AI is no longer restricted to experimental research environments but has become an operational component across healthcare, strategic management, finance, industrial engineering, cybersecurity, smart cities, and educational administration.

One of the most significant findings emerging from this review is the broad applicability of AI-driven decision support despite substantial differences among application domains. In healthcare, AI-based Clinical Decision Support Systems improve diagnostic accuracy, facilitate prognosis estimation, and assist clinicians in treatment planning while promoting personalized medicine. Business organizations employ intelligent analytical platforms to optimize forecasting, marketing strategies, and resource allocation. Financial institutions utilize predictive algorithms to strengthen liquidity management and reduce operational risk, whereas industrial sectors increasingly depend on machine learning for predictive maintenance and infrastructure reliability.

The evidence further indicates that technological performance alone does not determine implementation success. Across multiple independent investigations, organizational readiness, information quality, transparency, and explainability consistently emerge as decisive factors influencing user acceptance and long-term sustainability. High predictive accuracy provides limited practical value when decision-makers cannot understand or trust algorithmic recommendations. Consequently, Explainable Artificial Intelligence

(XAI) and Human-Centered Artificial Intelligence (HCAI) have become essential design principles rather than optional technical enhancements.

Another important observation concerns the ongoing transition from reactive decision support toward predictive intelligence. Traditional DSS primarily summarize historical information and generate descriptive reports. AI-enabled systems instead anticipate future events through machine learning, predictive analytics, neural networks, and adaptive reasoning mechanisms capable of continuously updating recommendations as new information becomes available. This shift fundamentally changes organizational decision-making by enabling proactive intervention rather than delayed response.

Despite these advantages, several challenges remain unresolved. Ethical concerns related to privacy, fairness, accountability, and algorithmic bias continue to influence implementation strategies across sensitive domains. Regulatory uncertainty and fragmented governance frameworks further complicate large-scale deployment, particularly in healthcare and public-sector environments where decisions directly affect human welfare. Moreover, many existing empirical studies evaluate AI systems under controlled institutional conditions, leaving questions regarding scalability and cross-cultural generalizability insufficiently explored.

The review also highlights a growing consensus that future Decision Support Systems should augment rather than replace human expertise. Collaborative intelligence models combining computational prediction with expert judgment appear better suited for complex decision environments characterized by uncertainty, ethical considerations, and contextual interpretation. Maintaining human oversight while leveraging AI's analytical capabilities represents a balanced strategy capable of maximizing both performance and accountability.

Overall, the synthesized evidence strongly supports the conclusion that Artificial Intelligence substantially enhances Decision Support Systems by improving analytical efficiency, predictive capability, and evidence-based reasoning across multiple sectors. Continued progress will likely depend on integrating advanced computational techniques with transparent governance structures, high-quality data ecosystems, explainable algorithms, and interdisciplinary collaboration. Such developments have the potential to establish AI-enabled DSS as indispensable instruments for intelligent decision-making in increasingly data-intensive societies.

## References

[1] M. Khosravi, Z. Zare, S. M. Mojtabaeian, and R. Izadi, “Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews,” *Health Services Research, Management and Epidemiology*, vol. 11, pp. 1–13, 2024.

[2] S. U. Hasan *et al.*, “A Systematic Review of AI-based Clinical Decision Support Systems: From Development and Implementation to Applications,” *Pakistan Journal of Life and Social Sciences*, vol. 23, no. 1, pp. 1482–1500, 2025.

[3] Q. Xu *et al.*, “Interpretability of Clinical Decision Support Systems Based on Artificial Intelligence from Technological and Medical Perspective: A Systematic Review,” *Journal of Healthcare Engineering*, vol. 2023, 2023.

[4] I. Bokhonko, M. Kubasiak, and A. Oleksa-Kaźmierczak, “Artificial Intelligence-Driven Decision Support Systems in Strategic Business Management: A Case-Based Analysis,” *Scientific Papers of Silesian University of Technology*, no. 230, pp. 49–61, 2025.

[5] S. Yang, "Artificial Intelligence Applications in Intelligent Financial Decision Support Systems: Integrating Big Data and Service Science for Supply Chain Finance Optimization," *Journal of Logistics, Informatics and Service Science*, vol. 13, no. 2, pp. 246–266, 2026.

[6] V. Vychuzhanin *et al.*, "Intelligent Decision Support System for Assessing the Risk of Technical Systems," *Scientific Reports*, vol. 23, 2024.

[7] N. Ma, "Artificial Intelligence-Driven Decision Support Systems for Sustainable Energy Management in Smart Cities," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 9, 2024.

[8] F. Shwedeh, "The Integration of Artificial Intelligence (AI) Into Decision Support Systems Within Higher Education Institutions," *Nanotechnology Perceptions*, vol. 20, no. S5, 2024.

[9] T. Tun *et al.*, "Health Care Workers' Trust in Artificial Intelligence–Based Clinical Decision Support Systems: Systematic Review," *Journal of Medical Internet Research*, vol. 27, p. e69678, 2025.

[10] M. Fanfani, L. A. I. Palesi, and P. Nesi, "Human-Centered AI for Decision Support Systems: A Systematic Review of Application Domains, Architecture Designs, Current Trends and Future Directions," *Big Data and Cognitive Computing*, vol. 10, no. 6, p. 186, 2026.

[11] S. Bozyel *et al.*, "Artificial Intelligence-Based Clinical Decision Support Systems in Cardiovascular Diseases," *Anatolian Journal of Cardiology*, vol. 28, no. 2, pp. 74–86, 2024.

[12] N. A. K. Aleessawi and L. Djaghrouri, "Artificial Intelligence in Decision-making: Literature Review," *Journal of the Association of Arab Universities for Research in Higher Education*, vol. 45, no. 1, 2025.

[13] H. Jalo *et al.*, "Early Identification and Characterisation of Stroke to Support Prehospital Decision-Making Using Artificial Intelligence," *BMJ Open*, vol. 13, no. 5, 2023.

[14] A. H. Khalaf, "Decision Support in Artificial Intelligence and Its Use in Objective Data," *J. Educ. Hum.*, vol. 5, pp. 778-802, 2025.

[15] V. Giaccone *et al.*, "Clinical Decision Support Systems for Chronic Low Back Pain and Lumbar Degenerative Conditions: A Systematic Review," *BMC Musculoskeletal Disorders*, vol. 26, no. 126, 2025.

[16] L. Taduri, "AI-Based Decision Support Systems for Healthcare Diagnostics: A Decision Support Framework," *International Journal for Research in Applied Science and Engineering Technology*, vol. 13, no. X, pp. 1868–1875, 2025.

[17] A. Abdelmouttalib *et al.*, "Artificial Intelligence Applications in Strategic Business Management," *Journal of Innovative Research and Business Studies*, vol. 1, no. 1, pp. 43–49, 2025.

[18] R. Joshi, V. Singh, and U. Sehgal, "A Systematic Review of Artificial Intelligence Enabled Data Driven Decision Making in Management and IT," *Journal of Neonatal Surgery*, vol. 14, no. 13, 2024.

[19] S. S. Andreevich, "Development of Intelligent Decision Support Systems in Small Business Consulting," *American Journal of Engineering and Technology*, vol. 7, no. 10, pp. 107–114, 2025.

[20] T. Mary and V. Rajendran, "Smart Decision Support in Industry: The Power of AI and Cognitive Computing," *International Journal of Science and Technology*, vol. 16, no. 4, pp. 1–14, 2025.

[21] O. Ali *et al.*, "A Systematic Literature Review of Artificial Intelligence in the Healthcare Sector: Benefits, Challenges, Methodologies, and Functionalities," *Journal of Innovation & Knowledge*, vol. 8, 2023.

[22] G. Nacouzi, O. A. Osoba, J. Tran, and S. Ishikawa, "Artificial Intelligence and Machine Learning Applications for Defensive Counterspace: A Decision Support Tool Capability Demonstration," RAND Corporation, RR-A582-1, 2023.

[23] L. Wang *et al.*, "Human-Centered Design and Evaluation of AI-Empowered Clinical Decision Support Systems: A Systematic Review," *Frontiers in Computer Science*, vol. 2, 2025.

# مراجعة منهجية لتطبيقات الذكاء الاصطناعي في نظم دعم القرار

**مصطفى عبد الهادي بن حميدة**
علوم الحاسوب، المعهد العالي للعلوم والتقنية، ليبيا

استلمت الورقة بتاريخ 2026/05/18، وقبلت بتاريخ 2026/06/10، ونشرت بتاريخ 2026/06/11

**الكلمات المفتاحية:**
الذكاء الاصطناعي
التعلم الآلي
نظم دعم القرار

**الملخص**

أصبح الذكاء الاصطناعي أحد أهم التقنيات الداعمة لتطوير أنظمة دعم القرار في مختلف القطاعات، هدفت هذه المراجعة المنهجية إلى تحليل وتلخيص نتائج 23 دراسة منشورة خلال الفترة 2023–2026 حول تطبيقات الذكاء الاصطناعي في أنظمة دعم القرار، أظهرت النتائج أن تقنيات الذكاء الاصطناعي، مثل تعلم الآلة والتعلم العميق والأنظمة الخبيرة والتحليلات التنبؤية والذكاء الاصطناعي القابل للتفسير، تسهم في تحسين دقة القرارات ورفع الكفاءة التشغيلية وتعزيز القدرة التنبؤية. وقد برز القطاع الصحي بوصفه المجال الأكثر استخدامًا لهذه التقنيات، حيث تُوظف في التشخيص والتنبؤ بالحالات المرضية وتخطيط العلاج. كما استفادت قطاعات الأعمال والتمويل من الذكاء الاصطناعي في التخطيط الاستراتيجي والتنبؤ وإدارة سلاسل الإمداد، بينما ركزت التطبيقات الصناعية على الصيانة التنبؤية وتقييم المخاطر، وعلى الرغم من هذه المزايا، لا تزال تحديات مثل جودة البيانات والخصوصية وشفافية الخوارزميات والاعتبارات الأخلاقية والتنظيمية تحد من التبني الواسع لهذه الأنظمة، وتؤكد النتائج أهمية التوجه نحو الذكاء الاصطناعي المتمحور حول الإنسان الذي يعزز التعاون بين الأنظمة الذكية والخبراء، وتخلص الدراسة إلى أن الذكاء الاصطناعي يمتلك قدرة كبيرة على تطوير أنظمة دعم القرار عند دعمه ببيانات موثوقة وحوكمة فعالة وخوارزميات شفافة.