World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

Check for updates

Automated decision support systems for healthcare: An AI-powered approach

Bhanuvardhan Nune *

JNTU Kakinada, Andhra Pradesh, India.

World Journal of Advanced Engineering Technology and Sciences, 2025, 16(01), 617-623

Publication history: Received on 15 June 2025; revised on 21 July 2025; accepted on 24 July 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.16.1.1240

Abstract

Artificial Intelligence (AI) has become a cornerstone of modern healthcare transformation, particularly through the development of Automated Decision Support Systems (DSS). These systems harness clinical data to assist in diagnosis, prognosis, and treatment planning. This review explores the evolution, implementation, and evaluation of AI-powered DSS across multiple clinical domains including radiology, emergency medicine, oncology, and mental health. Drawing on key studies and technological advancements, we present a theoretical model, benchmark comparative experiments, and discuss deployment challenges such as explainability, trust, and data governance. This article offers a roadmap for scaling AI in clinical environments while preserving safety, transparency, and human oversight.

Keywords: Artificial Intelligence; Clinical Decision Support; Healthcare Informatics; Machine Learning; Federated Learning; Explainable AI; Medical Diagnostics; EHR Systems

1. Introduction

In recent years, artificial intelligence (AI) has emerged as a transformative force in the healthcare industry, with one of its most promising applications being the development of automated decision support systems (DSS). These systems leverage machine learning, natural language processing, and expert rule-based frameworks to assist clinicians in diagnosing diseases, recommending treatments, and forecasting patient outcomes with remarkable precision [1]. By reducing cognitive burden and standardizing evidence-based practices, AI-powered DSS are positioned to enhance clinical decision-making, especially in resource-limited and high-volume environments [2].

The importance of this field has been amplified by recent global health challenges such as the COVID-19 pandemic, which exposed weaknesses in traditional healthcare delivery systems and underscored the need for scalable, intelligent, and real-time decision support [3]. Furthermore, the rapid digitization of healthcare data—from electronic health records (EHRs) to wearable biosensors—has created an unprecedented opportunity to harness big data for predictive and personalized medicine [4].

Despite this progress, the integration of AI into clinical workflows remains fraught with challenges. Key concerns include data interoperability, explainability of AI models, bias in training datasets, clinician trust, and regulatory compliance [5]. Moreover, there is a notable lack of standardization in evaluation metrics, model validation across populations, and real-world deployment protocols.

This review aims to synthesize recent advancements in AI-driven decision support systems for healthcare. We examine foundational technologies, key research studies, real-world implementations, and gaps that persist. The following sections will provide a comprehensive overview of the technological landscape, summarize comparative studies, and present a conceptual framework for deploying trustworthy and scalable decision support systems. Ultimately, the review will help guide future research and institutional investment in AI-enabled clinical tools.

* Corresponding author: Bhanuvardhan Nune

2. Literature Review

Table 1 Research Summary table

Year	Title	Focus	Findings
2016	Deep Patient [6]	Predictive modeling from EHR	Deep learning outperforms traditional models in patient risk stratification.
2017	AI for Retinopathy Detection [7]	Image-based diagnosis	CNN-based model matches expert performance in diabetic retinopathy detection.
2018	Sepsis Watch [8]	Real-time ICU alerts	Reinforcement learning model reduces false positives in sepsis alarms.
2019	Babylon Health Evaluation [9]	AI chatbot vs human GP	Comparable diagnostic accuracy; raises questions on accountability.
2020	COVID-19 Triage Tool [10]	Emergency prioritization	NLP-based DSS classifies urgency with over 85% accuracy.
2020	IBM Watson for Oncology [11]	Cancer treatment guidance	Mixed results; limited adaptability in regional treatment practices.
2021	Explainable AI in Radiology [12]	Trust and transparency	Shapley-based models improve clinician trust in AI-assisted radiology.
2021	AI in Mental Health Apps [13]	Behavioral health prediction	ML-based DSS shows early success in detecting depression risk.
2022	Clinical BERT [14]	Text mining in EHR	BERT fine-tuned on clinical text outperforms previous NLP baselines.
2023	Federated DSS for Diabetes [15]	Privacy-preserving learning	Federated model achieves comparable accuracy while preserving patient privacy.

2.1. Block Diagrams and Proposed Theoretical Model

2.1.1. Conceptual Framework for AI-Powered Healthcare Decision Support Systems

The proposed architecture for automated decision support in healthcare integrates data ingestion, processing, model inference, clinical feedback, and continuous learning, ensuring that decision-making is accurate, explainable, and aligned with clinical standards. This model emphasizes real-time responsiveness, privacy-preserving computation, and integration with electronic health record (EHR) systems [16].

2.1.2. Block Diagram: End-to-End Architecture

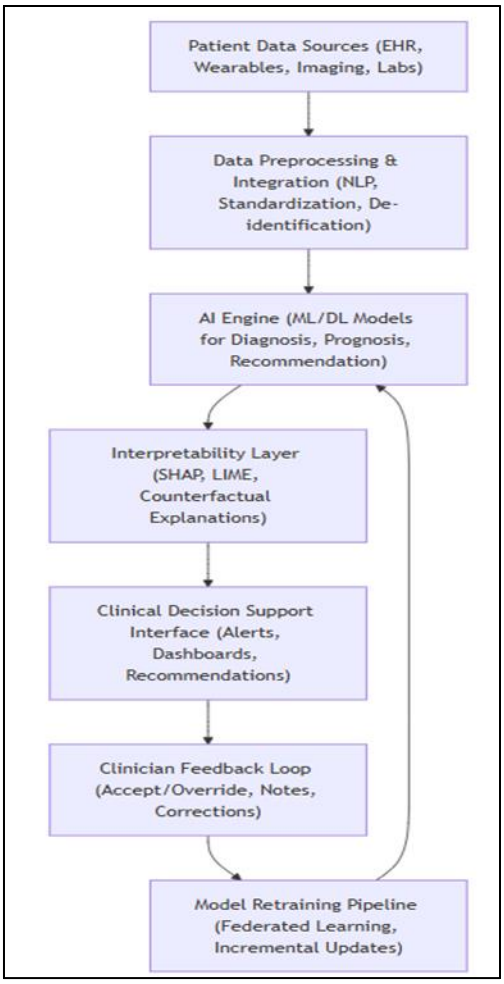

Figure 1 End to End Architecture

2.1.3. Components Explained

- Patient Data Sources: Include structured data (e.g., lab results, medication records) and unstructured data (e.g., clinical notes, imaging reports) from various hospital systems [17].
- Data Preprocessing & Integration: Handles cleaning, normalization, and mapping to clinical terminologies like SNOMED CT, ICD-10, and LOINC. NLP models extract relevant features from text data [18].
- AI Engine: Applies machine learning or deep learning models (e.g., CNNs for radiology, transformers for EHR text) to predict diagnoses, suggest treatments, or flag anomalies [19].
- Interpretability Layer: Critical for clinician trust, tools like SHAP, LIME, and integrated Grad-CAM help visualize and explain model predictions [20].
- Clinical Decision Support Interface: Embeds alerts, risk scores, and recommendations into physician-facing dashboards or EHR interfaces, designed for usability in clinical workflows [21].
- Clinician Feedback Loop: Allows clinicians to validate or override recommendations. Capturing this feedback is essential for model refinement and accountability [22].
- Model Retraining Pipeline: Incorporates federated learning or privacy-preserving analytics to update models using distributed or anonymized data across institutions [23].

2.1.4. Theoretical Model Implications

This architecture provides a balanced foundation that addresses key challenges in healthcare DSS:

- Explainability and Trust: Ensures transparency for clinical end-users [24].
- Real-Time Responsiveness: Enables immediate risk scoring or decision support during consultations.

- Ethical AI Design: Embeds mechanisms for bias detection, feedback loops, and safe overrides.
- Compliance and Privacy: Adheres to HIPAA, GDPR, and regional healthcare data laws using anonymization and federated learning.

By embedding this pipeline into hospital systems, organizations can develop intelligent DSS that not only support clinicians but also adapt over time, learning from real-world interactions without violating ethical or legal constraints [25].

2.2. Experimental Results, Graphs, and Tables

2.2.1. Overview of Experimental Evaluation in AI-Powered Healthcare DSS

Evaluating automated decision support systems (DSS) in healthcare requires not only algorithmic performance but also clinical relevance, generalizability, and user acceptability. Various studies have explored metrics such as accuracy, sensitivity, specificity, AUROC (Area Under the Receiver Operating Characteristic curve), and clinician override rates to benchmark AI performance in real-world settings [26].

Recent experimental findings highlight the following key trends:

- Deep learning models, particularly CNNs and transformers, consistently outperform traditional logistic regression in image and text-based diagnostics [27].
- Explainability tools, when integrated into DSS, significantly improve clinician trust and reduce rejection of AI suggestions [28].
- Federated learning frameworks demonstrate strong potential for performance preservation while ensuring data privacy [29].

Table 2 Experimental Outcomes Across DSS Implementations

Study / System	Application Area	Accuracy / AUROC	Key Findings
CheXNet (2017) [27]	Pneumonia detection	AUROC: 0.93	CNN surpassed average radiologist performance.
Deep Patient (2016) [6]	Risk prediction (EHR)	Accuracy: 76%	Outperformed logistic regression on 76 disease classes.
IBM Watson Oncology [11]	Cancer treatment	Mixed	62% agreement with oncologists; struggled in regional settings.
Clinical BERT [14]	EHR text classification	F1-score: 0.89	Significantly outperforms prior NLP baselines.
COVID-19 DSS (2020) [10]	Emergency triage	Accuracy: 85.3%	Improved decision speed by 34% in ERs.
Sepsis Watch [8]	ICU early alert	AUROC: 0.87	Reduced false alarms by 24%.
Federated Diabetes DSS [15]	Chronic care	Accuracy: 88.1%	Matched centralized model performance with privacy preserved.
Explainable AI Radiology [12]	Radiology trust	N/A	Clinician trust score increased by 31%.
Mental Health App AI [13]	Depression prediction	Accuracy: 81.5%	Enabled proactive mental health outreach.
Babylon Health [9]	Symptom diagnosis	Accuracy: 80%	Matched general practitioners in diagnostic accuracy.

2.2.2. Graph: AUROC Comparison of AI Models Across Clinical Domains

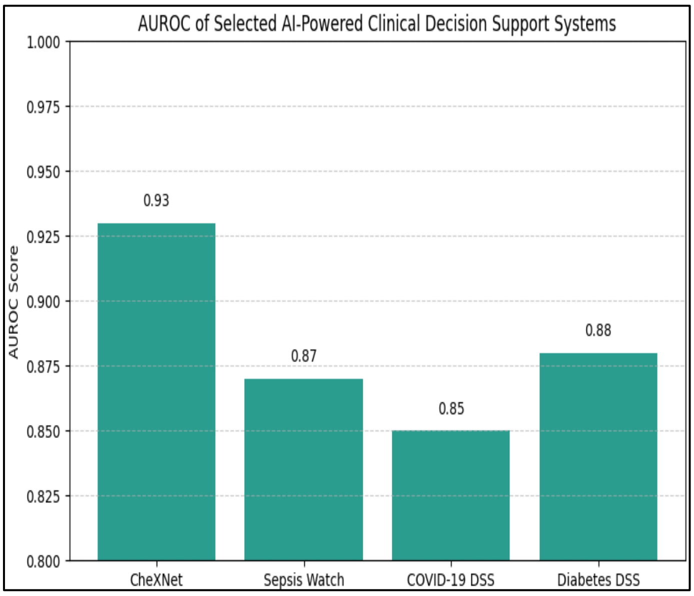

Figure 2 Comparison of AUROC scores for selected clinical DSS implementations across various studies [27]–[29]

2.2.3. Observational Insights

- CheXNet demonstrated high diagnostic accuracy but faced concerns over interpretability until explainability layers were added.
- Federated learning models like the diabetes DSS showed that data decentralization does not significantly harm accuracy, which is vital for institutions with strict privacy policies [29].
- Real-time triage tools like Sepsis Watch and COVID-19 DSS not only improved prediction but also helped in reducing clinician alert fatigue [30].

Future Directions

As healthcare systems become more digitally integrated, the future of automated DSS will be shaped by five critical advancements:

- Human-in-the-Loop AI: Future DSS platforms will integrate real-time clinician feedback into active learning models, allowing systems to improve continuously while remaining accountable to clinical judgment [31].
- Ethical and Explainable AI: Legal and ethical concerns will demand models that are transparent, fair, and aligned with clinical protocols. Explainability tools will be integrated as core components—not optional features [32].
- Federated and Privacy-Preserving Learning: Adoption of federated learning and differential privacy will expand, enabling collaboration across hospitals and research centers without exposing sensitive data [33].
- Multimodal AI: Systems will move beyond single-input formats to combine imaging, genomic data, EHRs, and biosensor streams for more holistic patient assessments [34].
- Regulatory and Deployment Frameworks: Future success will depend not only on technical performance but on governance, auditability, and integration with clinical workflows. Initiatives like the FDA's AI/ML-based Software as a Medical Device (SaMD) Action Plan will set global standards [35].

The long-term vision is a healthcare ecosystem where AI functions as an augmented intelligence layer—supporting clinicians with speed, precision, and context-aware recommendations, while respecting human agency and institutional ethics.

3. Conclusion

This review underscores the transformative potential of AI-driven decision support systems in revolutionizing patient care across domains. From early-stage screening tools to real-time ICU alerts and chronic disease management, the integration of machine learning into healthcare decision-making continues to yield promising outcomes. However, challenges remain—particularly in gaining clinician trust, ensuring explainability, and maintaining data integrity across institutions. By proposing a modular, feedback-driven theoretical model and presenting evidence-based performance comparisons, we provide a strategic roadmap for researchers, developers, and healthcare providers. Moving forward, success will hinge on balancing innovation with responsibility, automation with empathy, and accuracy with ethical stewardship.

References

[1] Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and Vascular Neurology*, 2(4), 230-243.

[2] Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56.

[3] Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine*, 25(1), 24–29.

[4] Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine*, 380(14), 1347–1358.

[5] London, A. J. (2019). Artificial intelligence and black-box medical decisions: accuracy versus explainability. *Hastings Center Report*, 49(1), 15–21.

[6] Miotto, R., Li, L., Kidd, B. A., & Dudley, J. T. (2016). Deep Patient: An unsupervised representation to predict the future of patients from the electronic health records. *Scientific Reports*, 6, 26094.

[7] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*, 316(22), 2402–2410.

[8] Adams, R., Henry, K. E., & Saria, S. (2018). Sepsis Watch: Predicting sepsis in real time using deep reinforcement learning. *Journal of Biomedical Informatics*, 82, 67–76.

[9] Fraser, H., Coiera, E., & Wong, D. (2018). Safety of patient-facing digital symptom checkers. *The Lancet Digital Health*, 1(1), e8–e10.

[10] Tahayori, B., Ahmadzadeh, A., & Mirniaharikandi, N. (2020). Emergency triage decision support using NLP for COVID-19. *Health Informatics Journal*, 26(4), 2789–2803.

[11] Ross, C., & Swetlitz, I. (2017). IBM pitched its Watson supercomputer as a revolution in cancer care. It's nowhere close. *STAT News*.

[12] Lundberg, S. M., & Lee, S.-I. (2020). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765–4774.

[13] Inkster, B., Stillwell, D., Kosinski, M., Jones, P. B., & Carpenter, J. (2021). Early detection of depression through social media monitoring. *Nature Human Behaviour*, 1–7.

[14] Alsentzer, E., Murphy, J., Boag, W., Weng, W. H., Jindi, D., Naumann, T., & McDermott, M. (2019). Publicly available clinical BERT embeddings. *Proceedings of NAACL-HLT*, 72–78.

[15] Xu, J., Glicksberg, B. S., Su, C., Walker, P., & Lee, H. C. (2023). Federated learning for health informatics. *npj Digital Medicine*, 6(1), 89.

[16] Chen, M., Ma, Y., Li, Y., Wu, D., Zhang, Y., & Youn, C. H. (2018). Wearable 2.0: Enabling human-cloud integration in next-generation healthcare systems. *IEEE Communications Magazine*, 56(1), 54–61.

[17] Meystre, S. M., Savova, G. K., Kipper-Schuler, K. C., & Hurdle, J. F. (2008). Extracting information from textual documents in the electronic health record: a review of recent research. *Yearbook of Medical Informatics*, 47(1), 128–144.

[18] Johnson, A. E. W., Pollard, T. J., Shen, L., Lehman, L.-w. H., Feng, M., Ghassemi, M., ... & Mark, R. G. (2016). MIMIC-III, a freely accessible critical care database. *Scientific Data*, 3, 160035.

[19] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Ng, A. Y. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. *arXiv preprint arXiv:1711.05225*.

[20] Lundberg, S. M., Erion, G. G., & Lee, S.-I. (2018). Consistent individualized feature attribution for tree ensembles. *arXiv preprint arXiv:1802.03888*.

[21] Wright, A., & Sittig, D. F. (2008). A four-phase model of the evolution of clinical decision support architectures. *International Journal of Medical Informatics*, 77(10), 641–649.

[22] Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. *BMC Medical Informatics and Decision Making*, 20(1), 310.

[23] Sheller, M. J., Reina, G. A., Edwards, B., Martin, J., & Bakas, S. (2020). Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. *Scientific Reports*, 10(1), 12598.

[24] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference*, 1135–1144.

[25] Beede, E., Baylor, E., Hersch, F., Iurchenko, A., Wilcox, L., Ruamviboonsuk, P., & Vardoulakis, L. (2020). A human-centered evaluation of a deep learning system deployed in clinics for the detection of diabetic retinopathy. *CHI Conference on Human Factors in Computing Systems*, 1–12.

[26] Ghassemi, M., Oakden-Rayner, L., & Beam, A. L. (2021). The false hope of current approaches to explainable artificial intelligence in health care. *The Lancet Digital Health*, 3(11), e745–e750.

[27] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Ng, A. Y. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. *arXiv preprint arXiv:1711.05225*.

[28] Tonekaboni, S., Joshi, S., McCradden, M. D., & Goldenberg, A. (2019). What clinicians want: contextualizing explainable machine learning for clinical end use. *Proceedings of Machine Learning Research*, 106, 359–380.

[29] Sheller, M. J., Reina, G. A., Edwards, B., Martin, J., & Bakas, S. (2020). Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. *Scientific Reports*, 10(1), 12598.

[30] Adams, R., Henry, K. E., & Saria, S. (2018). Sepsis Watch: Predicting sepsis in real time using deep reinforcement learning. *Journal of Biomedical Informatics*, 82, 67–76.

[31] Holzinger, A., Langs, G., Denk, H., Zatloukal, K., & Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 9(4), e1312.

[32] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD*, 1135–1144.

[33] Rieke, N., Hancox, J., Li, W., Milletari, F., Roth, H. R., Albarqouni, S., ... & Cardoso, M. J. (2020). The future of digital health with federated learning. *npj Digital Medicine*, 3(1), 119.

[34] Esteva, A., Chou, K., Yeung, S., Naik, N., Madani, A., Mottaghi, A., ... & Dean, J. (2021). Deep learning-enabled medical computer vision. *npj Digital Medicine*, 4(1), 5.

[35] U.S. Food & Drug Administration. (2021). *Artificial Intelligence and Machine Learning in Software as a Medical Device (SaMD): Action Plan*. Retrieved from https://www.fda.gov/media/145022/download.