

Artificial Intelligence in Infectious Diseases and Clinical Microbiology

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ABSTRACT

Artificial intelligence (AI) is increasingly influencing healthcare, with growing relevance in infectious diseases and clinical microbiology. This review summarizes current applications of machine learning (ML), deep learning (DL), and large language models (LLMs) in these areas while critically evaluating their strengths and limitations. Although AI has shown promising performance in image analysis, molecular diagnostics, risk prediction, and clinical decision support, its routine implementation remains constrained by limited external validation, heterogeneous datasets, algorithmic bias, and challenges in generalizability and explainability. The review also discusses AI's emerging role in scientific writing and the ethical and practical considerations associated with its clinical adoption. Overall, current evidence suggests that AI should be regarded as a complementary decision-support technology whose safe and effective integration depends on rigorous validation, high-quality data, and appropriate clinical oversight.

Keywords: Artificial intelligence, machine learning, deep learning, clinical decision support, antimicrobial stewardship

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THE DAWN OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE

Artificial intelligence (AI) is a branch of computer science that develops computational systems capable of performing tasks that typically require human intelligence, including pattern recognition, prediction, and decision support. Artificial intelligence has become increasingly integrated into healthcare, offering new opportunities to improve diagnostics, prognostic assessment, and clinical decision-making. Recent advances in machine learning (ML), deep learning (DL), and large language models (LLMs), together with the increasing availability of digital health data, have accelerated the development of AI applications across medicine (1).

In infectious diseases and clinical microbiology (IDCM), AI has attracted growing interest because it can improve laboratory diagnostics, antimicrobial stewardship, prognostic assessment, outbreak surveillance, and clinical decision support. Although numerous studies have reported promising results, important challenges related to external validation, data quality, model generalizability, and clinical implementation continue to limit the routine adoption of these technologies.

This review was prepared based on the thematic discussions, expert presentations, and literature evaluations conducted within the 2025 Basic Education Program of the Assistants and Young Specialists Commission of the Turkish Society of Clinical Microbiology and Infectious Diseases, entitled *AI in Infectious Diseases and Clinical Microbiology*. Building on these educational activities, this review critically synthesizes current evidence on AI applications in IDCM, highlighting both their clinical potential and the methodological, practical, and ethical challenges that must be addressed before widespread implementation.

THE ROLE OF AI IN MEDICINE

AI in medicine has evolved from early rule-based expert systems to modern ML and DL models capable of analyzing complex clinical data (2,3). These approaches have been widely adopted in specialties such as radiology and pathology, where

image-based analysis has demonstrated substantial clinical utility (4,5). In contrast, AI applications in IDCM remain at an earlier stage of implementation because they require integrating microbiological, clinical, and epidemiological information. Accordingly, AI systems in this field should be evaluated according to their specific clinical applications, evidence base, and limitations rather than as a single technology.

ML AND DL IN INFECTIOUS DISEASES AND CLINICAL MICROBIOLOGY

Machine learning and DL applications in IDCM have expanded rapidly over the past decade, driven by advances in computational methods and the increasing availability of digital laboratory and clinical data. Current applications can be broadly categorized into four major areas: diagnostic automation, clinical decision support, clinical documentation and symptom assessment, and epidemiological surveillance (Table 1). Although numerous studies have demonstrated promising results, most AI systems remain task-specific and have not yet undergone sufficient prospective or multicenter validation for routine clinical implementation.

Diagnostic Automation and Molecular Analysis

Diagnostic microbiology is among the most suitable areas for AI implementation because many laboratory procedures involve repetitive image interpretation and pattern-recognition tasks. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated high diagnostic performance in automated Gram stain interpretation and digital culture plate analysis, with reported agreement rates exceeding 95% under controlled experimental conditions (6). Nevertheless, further validation in diverse laboratory settings is required before widespread implementation.

Artificial intelligence has also advanced molecular diagnostics through automated analysis of whole-genome sequencing data. ML-based platforms, such as DeepARG and PARGT, enable rapid identification of antimicrobial resistance genes and facilitate genomic surveillance (7,8). However, their performance remains dependent on sequencing

Table 1. Classification of general clinical AI tools relevant to IDCM practice.

Category	Representative tools and systems	Clinical application in infectious diseases
CDSS	IBM Watson (Merative), Isabel Healthcare, DXplain, VisualDx, Sepsis Watch, Bayesian Health	Differential diagnosis of rare conditions, sepsis risk prediction, and providing actionable clinical guidance.
Symptom analyzers	Ada Health, Symptoma, Infermedica, Healthily, DxGPT (GPT-4)	Analysis of patient-reported symptoms for triage, rare disease identification, and mobile health integration.
Documentation and EHR systems	Suki AI, Nabla, Nuance DAX, DeepScribe, Epic Systems, Oracle Cerner	Automated clinical note generation, ICD-10 coding, sepsis monitoring, and complication prediction within EHRs.
Dermatological diagnostics	Skinive.MD, VisualDx	Classification of exanthematous lesions (e.g., mpox, varicella, measles) using CNNs.
Molecular and genomic AI	DeepARG, PathoFact, PARGT, Nextstrain, Pangolin	AMR gene prediction and real-time viral mutation visualization for epidemiological surveillance.

AI: Artificial intelligence, **AMR:** Antimicrobial resistance, **CNNs:** Convolutional neural networks, **CDSS:** Clinical decision support systems, **EHRs:** Electronic health records, **ICD-10:** International Classification of Diseases, 10th Revision.

quality, reference database completeness, and the continuous updating of resistance gene repositories.

Clinical Decision Support Systems

Clinical decision support systems (CDSS) integrate laboratory findings with clinical information to assist with diagnosis, risk prediction, and treatment decisions. AI-based sepsis prediction models, including Sepsis Watch and the Epic Sepsis Prediction Model (Epic Systems, Verona, WI, USA) and Epic's Sepsis Prediction Model, have demonstrated the potential to identify patients at increased risk before clinical deterioration occurs (9). However, inconsistent performance across institutions, false-positive alerts, and alert fatigue remain important barriers to routine implementation.

Similarly, AI-assisted diagnostic support platforms combine clinical findings with large medical knowledge bases to facilitate differential diagnosis, whereas natural language processing (NLP)-based applications improve access to evidence-based recommendations and clinical guidelines (10,11). Although these tools may improve efficiency, they should be regarded as supportive technologies rather than autonomous diagnostic systems.

Symptom Analyzers, Triage, and Documentation

Recent advances in NLP and LLMs have expanded AI applications to symptom assessment and clinical documentation. Symptom analyzers may assist with preliminary patient triage, whereas AI-powered documentation systems can automatically

generate clinical notes and reduce administrative workload (12–15). Despite these advantages, current LLM-based applications remain susceptible to hallucinations, incomplete contextual understanding, and variable performance across different clinical scenarios, emphasizing the need for careful clinician review.

Epidemiological Surveillance and Real-World Performance

Artificial intelligence has become an increasingly valuable tool for infectious disease surveillance by supporting genomic epidemiology, outbreak monitoring, and pathogen evolution analysis. Platforms such as Nextstrain have played an important role in monitoring viral evolution during the COVID-19 pandemic (16,17). At the same time, the pandemic highlighted the importance of representative datasets, continuous model updating, and external validation, demonstrating that algorithmic performance alone does not guarantee successful implementation in real-world public health settings (18–20).

FROM MICROSCOPE TO AI: CURRENT EVIDENCE ON AI MODELS IN MEDICAL PARASITOLOGY

Microscopic diagnosis remains the cornerstone of medical parasitology but is often labor-intensive and dependent on experienced personnel. Consequently, AI-based image analysis has emerged as a promising approach to improve diagnostic efficiency and standardization, particularly in settings with limited access to expert microscopists (21).

Current evidence is strongest for blood-borne parasites, particularly *Plasmodium* spp., where CNN-based models have consistently demonstrated high diagnostic accuracy under experimental conditions (22,23). Similar automated ML frameworks are being developed to identify intestinal parasites in stool samples. For instance, DL algorithms trained on large datasets of helminth eggs have shown significant potential to differentiate species with high morphological similarity, such as *Ascaris lumbricoides* and *Trichuris trichiura* (24).

More recently, multimodal LLMs, including GPT-4 and Gemini, have been explored for parasitological image interpretation. However, unlike CNN-based models specifically trained for image classification, these general-purpose systems have shown inconsistent performance in recognizing complex microscopic structures and remain susceptible to hallucinations, particularly when image quality or contextual information is limited (25).

Recent literature largely agrees that while advanced computational models offer promising support for education and second-opinion assessment, they cannot yet function as primary diagnostic tools in parasitology. Therefore, current evidence supports using AI as an adjunct to, rather than a replacement for, expert microscopic evaluation, particularly in diagnostically challenging cases (26).

DL IN THE DIAGNOSIS OF EXANTHEMATOUS INFECTIOUS DISEASES

Deep learning has been increasingly investigated for automated recognition of infectious skin diseases because visual lesion assessment is an important component of clinical diagnosis. Most studies have focused on CNN-based image classification models that can distinguish common exanthematous infections from non-infectious skin disorders (27,28).

Recent studies have explored CNN-based models for classifying infectious skin diseases, including mpox, Lyme disease, and measles (29–32). While these studies report promising diagnostic performance in controlled experimental settings, their generalizability to real-world clinical environments remains uncertain and requires further validation (33).

Deep learning-supported systems also hold potential in dermatology by improving diagnostic consistency in atypical presentations and supporting remote evaluation through tele dermatology applications (34). However, these systems' performance depends heavily on the quality, representativeness, and diversity of training datasets. A major limitation is algorithmic bias, particularly the underrepresentation of darker skin tones in publicly available datasets, which may reduce diagnostic accuracy across diverse populations (35,36).

In addition, many current DL models rely exclusively on visual inputs and do not incorporate critical clinical information such as associated symptoms (e.g., fever, pruritus) or disease course, which are essential for differentiating infectious exanthems from non-infectious conditions such as drug eruptions.

Several commercially available mobile applications provide AI-assisted assessment of skin lesions; however, they should be regarded as screening tools rather than diagnostic systems because performance varies by image quality, lesion characteristics, and patient population (35,36).

Future research should prioritize prospective multicenter validation and the integration of clinical, epidemiological, and imaging data to improve the robustness and clinical applicability of AI models for infectious skin diseases.

AI-BASED ANTIMICROBIAL MANAGEMENT

Antimicrobial stewardship (AMS) is one of the most promising applications of AI in infectious diseases because it requires the integration of microbiological, clinical, and epidemiological data to support timely treatment decisions. Current AI applications focus primarily on optimizing empirical antibiotic selection, identifying patients at increased risk of resistant infections, and supporting antimicrobial prescribing through CDSS (37,38).

ML models, particularly those analyzing longitudinal electronic health record data, have demonstrated encouraging performance in predicting healthcare-associated infections and identifying

patients at high risk of multidrug-resistant organism (MDRO) infections, including carbapenem-resistant Enterobacterales (CRE) (39,40). These models may enable earlier risk stratification than conventional clinical scoring systems and support more targeted empirical antimicrobial therapy. However, most available evidence originates from retrospective studies, and prospective validation across different healthcare settings remains limited.

Although DL models can identify complex relationships within large clinical datasets, their predictions are often difficult to interpret in routine clinical practice. Explainable AI (XAI) approaches may help clinicians understand which variables contribute most to model predictions and thereby improve confidence in AI-assisted recommendations. However, XAI does not provide complete transparency into the internal processes of complex models and should not be interpreted as establishing causal relationships (41–43).

Large language models have recently emerged as potential AMS tools by summarizing clinical guidelines, assisting with literature retrieval, and supporting educational activities. Nevertheless, current LLMs remain susceptible to hallucinations, outdated knowledge, and limited access to real-time patient-specific information, limiting their use for independent therapeutic decision-making (44,45).

Overall, current evidence suggests that AI has considerable potential to optimize AMS by improving risk prediction and supporting antimicrobial prescribing. However, despite encouraging predictive performance, robust evidence demonstrating improvements in prescribing quality, antimicrobial consumption, or patient outcomes remains limited. Future progress will depend on high-quality clinical data, rigorous external validation, and successful integration of AI tools into AMS programs and routine clinical workflows (46).

ML APPLICATIONS IN PREDICTING THE PROGNOSIS OF INFECTIOUS DISEASES

Predicting disease progression is one of the most promising AI applications in infectious diseases because timely risk stratification can improve

patient management and resource allocation. Unlike diagnostic models, prognostic models aim to estimate future clinical outcomes by integrating clinical, laboratory, and increasingly multi-omics data. Recent advances in multi-omics technologies have enabled the integration of genomic, transcriptomic, proteomic, metabolomic, and conventional clinical data into ML-based prognostic models, supporting more individualized risk prediction (47,48).

Machine learning algorithms, including Random Forest, Support Vector Machines (SVM), and gradient boosting methods such as XGBoost, have been applied to predict outcomes in sepsis, COVID-19, and Crimean-Congo hemorrhagic fever (CCHF) by integrating clinical and molecular data (47–50). For instance, in targeted metabolomic analyses of patients with CCHF, ML models have been used to analyze amino acid profiles, enabling the prediction of intensive care requirements with high reported accuracy. In parallel, specialized computational frameworks have facilitated biomarker discovery using transcriptomic and metabolomic datasets, expanding opportunities for precision prognostic modeling (50).

Despite these encouraging findings, most prognostic models have been developed using retrospective datasets and lack prospective external validation. Challenges related to data imbalance, heterogeneous patient populations, and differences in clinical practice continue to limit model generalizability. Future studies should prioritize multicenter validation, standardized reporting, and assessment of clinical impact to determine whether improved predictive performance translates into better patient outcomes.

AI IN SCIENTIFIC WRITING AND SCHOLARLY PUBLISHING

Artificial intelligence is increasingly incorporated into the research and publication process, supporting activities ranging from literature retrieval and evidence synthesis to manuscript preparation and editorial screening. Unlike clinical decision-support applications, these tools primarily aim to improve research efficiency rather than generate new scientific evidence. Their growing adoption has also

raised important questions regarding transparency, accountability, and responsible use. AI-powered literature discovery platforms use NLP and citation network analysis to facilitate literature screening, identify relevant publications, and support evidence synthesis (51). Although these applications can substantially reduce literature review time, researchers still need to appraise their output critically. The ethical framework and permissible use cases of AI in scientific publishing are summarized in Table 2.

Beyond literature discovery, LLM-based applications are increasingly utilized for document analysis, including summarizing scientific manuscripts, extracting key findings, and assisting in evidence synthesis. These tools may enhance researchers' ability to process large volumes of clinical data; however, their outputs require careful verification because LLMs may generate inaccurate interpretations, unsupported statements, or fabricated references (52).

Furthermore, LLMs such as ChatGPT and Claude are increasingly used as writing assistants to improve grammar, language fluency, and manuscript organization. They may be particularly valuable for researchers writing in a second language by facilitating clearer scientific communication. Nevertheless, authors should always critically review and edit AI-generated text to ensure scientific accuracy and appropriate interpretation (53).

Publishers increasingly employ AI-assisted tools to detect plagiarism, image manipulation, and

potential ethical concerns during manuscript screening (54). Leading editorial organizations, including the International Committee of Medical Journal Editors (ICMJE) and the World Association of Medical Editors (WAME), have issued clear guidance stating that LLMs cannot be credited as authors, as they lack accountability, responsibility, and the capacity to provide informed consent (55–58).

Transparency regarding AI use has become a fundamental principle of responsible scientific publishing. Current editorial policies require authors to disclose the use of AI-assisted technologies during manuscript preparation while maintaining full responsibility for the accuracy, interpretation, and integrity of the published work (53–58). In parallel, emerging reporting frameworks, such as the ChatGPT, generative artificial intelligence and natural large language models for accountable reporting and use (CANGARU) guidelines, aim to standardize the responsible use and reporting of generative AI in research, emphasizing the need for human oversight throughout the scientific publication process (58). As these technologies continue to evolve, standardized reporting and transparent disclosure will be essential to ensure scientific credibility and maintain trust in AI-assisted research.

CURRENT CHALLENGES AND LIMITATIONS OF AI IN CLINICAL PRACTICE

Despite the rapid expansion of AI applications in healthcare, several methodological, technical, and ethical challenges continue to limit their routine

Table 2. Ethical framework and use cases of AI in scientific publishing.

Academic task	AI functionality and assistance	Editorial and ethical policy
Literature review	Summarizing articles, conducting open-ended queries, and mapping citations.	Permitted for synthesis; requires rigorous verification of source accuracy.
Manuscript editing	Grammar checking, proofreading, and stylistic refinement.	Generally permitted; mandates transparent disclosure in the manuscript.
Reference management	Automated in-text citations and bibliographic formatting.	Permitted; authors remain fully accountable for all cited materials.
Data interpretation	Generating original hypotheses or interpreting clinical data.	Restricted: AI must not replace human intellectual contribution.
Authorship claims	Crediting AI as a co-author.	Prohibited: AI lacks accountability and capacity for informed consent.
Peer review	Using AI for manuscript triaging or evaluating submissions.	Prohibited: Risk of confidentiality breaches and dissemination of false information.

implementation in IDCM. Clinical decision-making is inherently multidimensional, requiring integration of patient-specific factors, comorbidities, microbiological findings, and clinical context that algorithmic models may not fully capture (59). Key characteristics of black-box and explainable AI approaches relevant to clinical practice are summarized in Table 3.

Technical and Methodological Limitations

The performance of AI models depends heavily on the quality, completeness, and representativeness of the data used for model development. Although many studies have reported excellent predictive performance, most published models have been developed and validated using retrospective datasets from single institutions, limiting their generalizability across different healthcare settings (60). Differences in patient populations, disease prevalence, laboratory practices, and healthcare infrastructure may substantially affect model performance when AI systems are applied outside their original development environment.

Another important challenge is dataset shift, whereby changes in patient characteristics, pathogen epidemiology, diagnostic practices, or clinical workflows reduce the accuracy of previously developed models over time. These limitations are particularly relevant in infectious diseases, where evolving pathogens, emerging antimicrobial resistance, and changing treatment strategies continuously alter the clinical landscape. Table 4 summarizes the practical implications of these challenges for AI-based sepsis prediction systems

and their major limitations compared with traditional clinical scores.

In addition, many AI models are evaluated primarily using measures of predictive performance, such as discrimination or accuracy, without adequately assessing their impact on clinical decision-making or patient outcomes. Consequently, excellent performance in retrospective validation studies does not necessarily translate into meaningful clinical benefit in routine practice. Future research should therefore prioritize prospective multicenter validation, standardized reporting, and evaluation of clinical effectiveness alongside algorithmic performance (60).

Bias, Fairness, and Equity

Artificial intelligence systems may inadvertently reproduce or amplify biases present in the datasets used for model development, resulting in unequal performance across different patient populations (61). Such biases may arise from underrepresentation of specific demographic groups, differences in disease prevalence, incomplete clinical data, or the use of proxy variables that fail to accurately reflect patients' healthcare needs.

A well-recognized example is the Optum algorithm, which underestimated the healthcare needs of Black patients because healthcare expenditure was used as a proxy for illness severity rather than direct measures of health status (61). Similar concerns have been reported in medical imaging, where AI models trained predominantly on lighter skin tones demonstrated reduced diagnostic accuracy

Table 3. Comparative analysis of black-box versus white-box AI architectures.

Feature	Black-box AI (e.g., Epic SPM)	White-box / Explainable AI (XAI)
Transparency	Internal decision-making processes are opaque and nontraceable.	Decision logic and causality are transparent to the user.
Clinical reliability	May cause "alert fatigue" due to high false-positive rates.	Enhances diagnostic confidence through evidence-based explanations.
Ethical alignment	Challenges informed consent and patient autonomy.	Aligns with WHO principles of accountability and transparency.
User trust	Difficult for clinicians to verify the rationale behind alarms.	Allows clinicians to understand and validate the system's reasoning.
Example systems	SPMs	Kahun Medical, Medwise (NLP-guided evidence)

NLP: Natural language processing, **SPM:** Sepsis prediction model(s), **XAI:** Explainable artificial intelligence, **WHO:** World Health Organization.

Table 4. Performance comparison of sepsis prediction models: AI-based SPM versus traditional clinical scores.

Scoring system / Model	Methodology	Interpretability	Clinical utility and reliability
ML-based models (e.g., Epic SPM)	Data-driven (ML)	Non-explainable (Black-box)	High sensitivity but prone to alert fatigue and delayed interventions in some settings (9).
SOFA score	Clinical Rules	Explainable (White-box)	High; considered the gold standard for organ dysfunction but requires lab results.
SIRS criteria	Clinical Rules	Explainable (White-box)	High sensitivity for early screening; limited specificity (high false positives).

AI: Artificial intelligence, **ML:** Machine learning, **SIRS:** Systemic inflammatory response syndrome, **SOFA:** Sequential Organ Failure Assessment, **SPM:** Sepsis prediction model(s).

in individuals with darker skin pigmentation (36). These examples illustrate that algorithmic performance may not be uniform across populations and highlight the importance of evaluating AI systems for fairness before clinical implementation (62).

Reducing algorithmic bias requires diverse, representative datasets, continuous post-implementation monitoring, and external validation across different populations and healthcare settings. Incorporating fairness assessments into model development and evaluation is therefore essential to promote equitable and reliable AI-assisted healthcare.

Explainability and Clinical Trust

Many AI systems, particularly DL models, remain difficult to interpret because their internal decision-making processes are not directly observable. XAI methods aim to explain which variables or features influence model predictions and may improve clinicians’ confidence in AI-assisted recommendations. However, XAI does not necessarily provide complete transparency into model behavior, establish causal relationships, or fully explain how complex models generate their predictions (63).

These challenges have also been observed in real-world implementations. For example, the Epic sepsis prediction model showed limitations, including delayed alerts and high false-positive rates, which contributed to alert fatigue and reduced clinician confidence in the system (9). These experiences highlight the importance of rigorous clinical evaluation, continuous monitoring, and careful integration of AI systems into existing healthcare workflows.

Ethical and Human Factors

Beyond technical performance, implementing AI in healthcare raises important ethical and professional considerations. The World Health Organization has identified key principles for the responsible use of AI in health, including respect for human autonomy, beneficence, non-maleficence, transparency, accountability, inclusiveness, and sustainability (64). Adherence to these principles is essential to ensure that AI technologies are implemented safely, ethically, and equitably.

Although AI can support clinical decision-making by rapidly analyzing large volumes of data, it cannot fully replicate human judgment, empathy, ethical reasoning, or effective communication with patients. These human attributes remain particularly important when managing complex clinical situations, communicating diagnostic uncertainty, or making value-sensitive treatment decisions. Consequently, AI should be regarded as a tool that supports, rather than replaces, clinical expertise.

Taken together, these limitations suggest that the major challenge facing AI is no longer algorithm development alone, but generating robust clinical evidence demonstrating safe, equitable, and effective implementation in routine clinical practice. Future research should therefore emphasize prospective multicenter validation, transparent reporting, fairness assessment, and evaluation of clinical impact rather than predictive accuracy alone.

CONCLUSION AND FUTURE DIRECTIONS

Artificial intelligence is rapidly reshaping many aspects of IDCM, with applications spanning

diagnostic microbiology, prognostic modeling, antimicrobial stewardship, epidemiological surveillance, and scientific research. Current evidence indicates that AI can improve data analysis efficiency, support clinical decision-making, and facilitate the interpretation of increasingly complex clinical and laboratory information. However, evidence strength varies considerably across applications, and many reported models have yet to demonstrate consistent clinical benefit in routine practice.

The successful integration of AI into infectious diseases will depend not only on continued technological advances but also on the availability of high-quality and representative datasets, rigorous external validation, transparent reporting, careful evaluation of clinical impact, and adherence

to ethical principles. Importantly, future research should move beyond reporting predictive accuracy alone and focus on whether AI-assisted systems improve patient outcomes, antimicrobial prescribing, healthcare efficiency, and health equity across diverse populations.

Rather than replacing clinicians, AI should be viewed as a complementary technology that supports evidence-based decision-making while preserving the essential role of clinical expertise, professional judgment, and patient-centered care. Close collaboration among clinicians, microbiologists, data scientists, and policymakers will be essential to ensure that AI is implemented safely, responsibly, and in a manner that delivers meaningful benefits to patients and healthcare systems.

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REFERENCES

- 1 Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. *Nat Biomed Eng.* 2018;2(10):719–31. [\[CrossRef\]](#)
- 2 Naylor CD. On the prospects for a (deep) learning health care system. *JAMA.* 2018;320(11):1099–100. [\[CrossRef\]](#)
- 3 Mintz Y, Brodie R. Introduction to artificial intelligence in medicine. *Minim Invasive Ther Allied Technol.* 2019;28(2):73–81. [\[CrossRef\]](#)
- 4 Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. *Nat Rev Cancer.* 2018;18(8):500–10. [\[CrossRef\]](#)
- 5 Bera K, Schalper KA, Rimm DL, Velcheti V, Madabhushi A. Artificial intelligence in digital pathology - new tools for diagnosis and precision oncology. *Nat Rev Clin Oncol.* 2019;16(11):703–15. [\[CrossRef\]](#)
- 6 Smith KP, Kang AD, Kirby JE. Automated interpretation of blood culture Gram stains by use of a deep convolutional neural network. *J Clin Microbiol.* 2018;56(3):e01521-17. [\[CrossRef\]](#)
- 7 Arango-Argoty G, Garner E, Pruden A, Heath LS, Vikesland P, Zhang L. DeepARG: a deep learning approach for predicting antibiotic resistance genes from metagenomic data. *Microbiome.* 2018;6(1):23. [\[CrossRef\]](#)
- 8 Chowdhury AS, Call DR, Broschat SL. PARGT: a software tool for predicting antimicrobial resistance in bacteria. *Sci Rep.* 2020;10(1):11033. [\[CrossRef\]](#)
- 9 Wong A, Otles E, Donnelly JP, Krumm A, McCullough J, DeTroyer-Cooley O, et al. External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients. *JAMA Intern Med.* 2021;181(8):1065–70. Erratum in: *JAMA Intern Med.* 2021;181(8):1144. [\[CrossRef\]](#)
- 10 Miyachi Y, Ishii O, Torigoe K. Design, implementation, and evaluation of the computer-aided clinical decision support system based on learning-to-rank: collaboration between physicians and machine learning in the differential diagnosis process. *BMC Med Inform Decis Mak.* 2023;23(1):26. [\[CrossRef\]](#)

- 11 Berge GT, Granmo OC, Tveit TO, Munkvold BE, Ruthjersen AL, Sharma J. Machine learning-driven clinical decision support system for concept-based searching: a field trial in a Norwegian hospital. *BMC Med Inform Decis Mak.* 2023;23(1):5. [\[CrossRef\]](#)
- 12 Fraser H, Crossland D, Bacher I, Ranney M, Madsen T, Hilliard R. Comparison of diagnostic and triage accuracy of ada health and WebMD symptom checkers, ChatGPT, and physicians for patients in an emergency department: clinical data analysis study. *JMIR Mhealth Uhealth.* 2023;11:e49995. [\[CrossRef\]](#)
- 13 do Olmo J, Logroño J, Mascías C, Martínez M, Isla J. Assessing DxGPT: diagnosing rare diseases with various large language models. *medRxiv [Preprint]* 2024: 2024.05.08.24307062. [\[Cross-Ref\]](#)
- 14 Gaber F, Shaik M, Allega F, Bilecz AJ, Busch F, Goon K, et al. Evaluating large language model workflows in clinical decision support for triage and referral and diagnosis. *NPJ Digit Med.* 2025;8(1):263. [\[CrossRef\]](#)
- 15 Hager P, Jungmann F, Holland R, Bhagat K, Hubrecht I, Knauer M, et al. Evaluation and mitigation of the limitations of large language models in clinical decision-making. *Nat Med.* 2024;30(9):2613–22. [\[CrossRef\]](#)
- 16 Hadfield J, Megill C, Bell SM, Huddleston J, Potter B, Callender C, et al. Nextstrain: real-time tracking of pathogen evolution. *Bioinformatics.* 2018;34(23):4121–3. [\[CrossRef\]](#)
- 17 O'Toole Á, Scher E, Underwood A, Jackson B, Hill V, McCrone JT, et al. Assignment of epidemiological lineages in an emerging pandemic using the pangolin tool. *Virus Evol.* 2021;7(2):veab064. [\[CrossRef\]](#)
- 18 Wynants L, Van Calster B, Collins GS, Riley RD, Heinze G, Schuit E, et al. Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal. *BMJ.* 2020;369:m1328. Update in: *BMJ.* 2021;372:n236. Erratum in: *BMJ.* 2020;369:m2204. [\[CrossRef\]](#)
- 19 Hill A, Morrissey D, Marsh W. What characteristics of clinical decision support system implementations lead to adoption for regular use? A scoping review. *BMJ Health Care Inform.* 2024;31(1):e101046. [\[CrossRef\]](#)
- 20 Kim SY, Kim DH, Kim MJ, Ko HJ, Jeong OR. XAI-based clinical decision support systems: a systematic review. *Appl Sci.* 2024;14(15):6638. [\[CrossRef\]](#)
- 21 Kumar S, Arif T, Alotaibi AS, Malik MB, Manhas J. Advances towards automatic detection and classification of parasites microscopic images using deep convolutional neural network: methods, models and research directions. *Arch Comput Methods Eng.* 2023;30(3):2013–39. [\[CrossRef\]](#)
- 22 Rajaraman S, Antani SK, Poostchi M, Silamut K, Hossain MA, Maude RJ, et al. Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images. *PeerJ.* 2018;6:e4568. [\[CrossRef\]](#)
- 23 Bibin D, Nair MS, Punitha P. Malaria parasite detection from peripheral blood smear images using deep belief networks. *IEEE Access.* 2017;5:9099–108. [\[CrossRef\]](#)
- 24 Oyibo P, Meulah B, Agbana T, van Lieshout L, Oyibo W, Vdovin G, et al. Deep learning-based automated detection and multiclass classification of soil-transmitted helminths and *Schistosoma mansoni* eggs in fecal smear images. *Sci Rep.* 2025;15(1):21495. [\[CrossRef\]](#)
- 25 Nori H, King N, McKinney SM, Carignan D, Horvitz E. Capabilities of GPT-4 on medical challenge problems. *arXiv.* 2023;2303.13375. [\[CrossRef\]](#)
- 26 Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med.* 2019;25(1):44–56. [\[CrossRef\]](#)
- 27 Carin L, Pencina MJ. On deep learning for medical image analysis. *JAMA.* 2018;320(11):1192–3. [\[CrossRef\]](#)
- 28 Jeong HK, Park C, Henao R, Kheterpal M. Deep learning in dermatology: a systematic review of current approaches, outcomes, and limitations. *JID Innov.* 2022;3(1):100150. [\[CrossRef\]](#)
- 29 Hossain SI, de Goër de Herve J, Hassan MS, Martineau D, Petrosyan E, Corbin V, et al. Exploring convolutional neural networks with transfer learning for diagnosing Lyme disease from skin lesion images. *Comput Methods Programs Biomed.* 2022;215:106624. [\[CrossRef\]](#)
- 30 Khafaga DS, Ibrahim A, El-Kenawy EM, Abdelhamid AA, Karim FK, Mirjalili S, et al. An AI-Biruni Earth radius optimization-based deep convolutional neural network for classifying monkeypox disease. *Diagnostics (Basel).* 2022;12(11):2892. [\[CrossRef\]](#)
- 31 Furqon A, Malik K, Fajri FN. Detection of eight skin diseases using convolutional neural network with MobileNetV2 Architecture for identification and treatment recommendation on android application. *J Ilm Tek Elektro Komput Dan Inform.* 2024;10(2):373–84. [\[CrossRef\]](#)
- 32 Glock K, Napier C, Gary T, Gupta V, Gigante J, Schaffner W, et al. Measles rash identification using transfer learning and deep convolutional neural networks. *Proc IEEE Int Conf Big Data.* 2021:3905–10. [\[CrossRef\]](#)
- 33 Savaş S. Enhancing disease classification with deep learning: a two-stage optimization approach for monkeypox and similar skin lesion diseases. *J Imaging Inform Med.* 2024;37(2):778–800. [\[CrossRef\]](#)
- 34 Shapiro J, Lyakhovitsky A. Revolutionizing teledermatology: Exploring the integration of artificial intelligence, including Generative Pre-trained Transformer chatbots for artificial intelligence-driven anamnesis, diagnosis, and treatment plans. *Clin Dermatol.* 2024;42(5):492–7. [\[CrossRef\]](#)
- 35 Daneshjou R, Vodrahalli K, Novoa RA, Jenkins M, Liang W, Rotemberg V, et al. Disparities in dermatology AI performance on a diverse, curated clinical image set. *Sci Adv.* 2022;8(32):eabq6147. [\[CrossRef\]](#)
- 36 Daneshjou R, Smith MP, Sun MD, Rotemberg V, Zou J. Lack of transparency and potential bias in artificial intelligence data sets and algorithms: a scoping review. *JAMA Dermatol.* 2021;157(11):1362–9. [\[CrossRef\]](#)
- 37 AlGain S, Marra AR, Kobayashi T, Marra PS, Celeghini PD, Hsieh MK, et al. Can we rely on artificial intelligence to guide antimicrobial therapy? A systematic literature review. *Antimicrob Steward Healthc Epidemiol.* 2025;5(1):e90. [\[CrossRef\]](#)

- 38 Giacobbe DR, Marelli C, Guastavino S, Signori A, Mora S, Rosso N, et al. Artificial intelligence and prescription of antibiotic therapy: present and future. *Expert Rev Anti Infect Ther*. 2024;22(10):819–33. [\[CrossRef\]](#)
- 39 Garcia-Vidal C, Puerta-Alcalde P, Cardozo C, Orellana MA, Besanson G, Lagunas J, et al; ID-INNOVATION study group. Machine learning to assess the risk of multidrug-resistant Gram-negative bacilli infections in febrile neutropenic hematological patients. *Infect Dis Ther*. 2021;10(2):971–83. [\[CrossRef\]](#)
- 40 Nigo M, Rasmy L, Mao B, Kannadath BS, Xie Z, Zhi D. Deep learning model for personalized prediction of positive MRSA culture using time-series electronic health records. *Nat Commun*. 2024;15(1):2036. [\[CrossRef\]](#)
- 41 Giacobbe DR, Bassetti M. The fading structural prominence of explanations in clinical studies. *Int J Med Inform*. 2025;197:105835. [\[CrossRef\]](#)
- 42 Cavallaro M, Moran E, Collyer B, McCarthy ND, Green C, Keeling MJ. Informing antimicrobial stewardship with explainable AI. *PLOS Digit Health*. 2023;2(1):e0000162. [\[CrossRef\]](#)
- 43 Ali S, Akhlaq F, Imran AS, Kastrati Z, Daudpota SM, Moosa M. The enlightening role of explainable artificial intelligence in medical & healthcare domains: A systematic literature review. *Comput Biol Med*. 2023;166:107555. [\[CrossRef\]](#)
- 44 Giacobbe DR, Marelli C, La Manna B, Padua D, Malva A, Guastavino S, et al. Advantages and limitations of large language models for antibiotic prescribing and antimicrobial stewardship. *NPJ Antimicrob Resist*. 2025;3(1):14. [\[CrossRef\]](#)
- 45 Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat Mach Intell*. 2019;1(5):206–15. [\[CrossRef\]](#)
- 46 He H, Huang T, Guo S, Yu F, Shen H, Shao H, et al. Identification of a novel sepsis prognosis model and analysis of possible drug application prospects: Based on scRNA-seq and RNA-seq data. *Front Immunol*. 2022;13:888891. [\[CrossRef\]](#)
- 47 Iftimie S, Amigó N, Martínez-Micaelo N, López-Azcona AF, Martínez-Navidad C, Castañé H, et al. Differential analysis of lipoprotein and glycoprotein profiles in bacterial infections and COVID-19 using proton nuclear magnetic resonance and machine learning. *Heliyon*. 2024;10(17):e37115. [\[CrossRef\]](#)
- 48 Mikaeloff F, Gelpi M, Benfeitas R, Knudsen AD, Vestad B, Høgh J, et al. Network-based multi-omics integration reveals metabolic at-risk profile within treated HIV-infection. *eLife*. 2023;12:e82785. [\[CrossRef\]](#)
- 49 Goksuluk D, Zararsiz G, Korkmaz S, Eldem V, Zararsiz GE, Ozcetin E, et al. MLSeq: Machine learning interface for RNA-sequencing data. *Comput Methods Programs Biomed*. 2019;175:223–31. [\[CrossRef\]](#)
- 50 Zararsiz G, Goksuluk D, Klaus B, Korkmaz S, Eldem V, Karabulut E, et al. voomDDA: discovery of diagnostic biomarkers and classification of RNA-seq data. *PeerJ*. 2017;5:e3890. [\[CrossRef\]](#)
- 51 Fodouop Kouam AW. AI in academic writing: ally or foe? *Int J Res Publ*. 2024;148(1):353–8. [\[CrossRef\]](#)
- 52 Flanagan A, Bibbins-Domingo K, Berkwits M, Christiansen SL. Nonhuman "authors" and implications for the integrity of scientific publication and medical knowledge. *JAMA*. 2023;329(8):637–9. [\[CrossRef\]](#)
- 53 Stokel-Walker C. ChatGPT listed as author on research papers: many scientists disapprove. *Nature*. 2023;613(7945):620–1. [\[CrossRef\]](#)
- 54 Elsevier. The use of generative AI and AI-assisted technologies in the review process for Elsevier [Internet]. Amsterdam: Elsevier; May 15, 2024. [cited August 11, 2025]. Available from: <https://www.elsevier.com/en-in/about/policies-and-standards/the-use-of-generative-ai-and-ai-assisted-technologies-in-the-review-process>
- 55 Bobier C, Rodger D, Hurst D. Artificial intelligence policies in bioethics and health humanities: a comparative analysis of publishers and journals. *BMC Med Ethics*. 2025;26(1):79. [\[CrossRef\]](#)
- 56 International Committee of Medical Journal Editors (ICMJE). Recommendations for the Conduct, Reporting, Editing, and Publication of Scholarly Work in Medical Journals [Internet]. Philadelphia (PA): International Committee of Medical Journal Editors; Updated January 2026. [cited May 5, 2026]. Available from: <https://www.icmje.org/icmje-recommendations.pdf>
- 57 Zielinski C, Winker MA, Aggarwal R, Ferris LE, Heinemann M, Lapeña JF Jr, et al. Chatbots, generative AI, and scholarly manuscripts: WAME recommendations on chatbots and generative artificial intelligence in relation to scholarly publications. *Columbia Med (Cali)*. 2023;54(3):e1015868. [\[CrossRef\]](#)
- 58 Cacciamani GE, Eppler MB, Ganjavi C, Pekan A, Biedermann B, Collins GS, et al. Development of the ChatGPT, generative artificial intelligence and natural large language models for accountable reporting and use (CANGARU) guidelines. *arXiv*. 2023;2307.08974. [\[CrossRef\]](#)
- 59 Wiens J, Shenoy ES. Machine learning for healthcare: on the verge of a major shift in healthcare epidemiology. *Clin Infect Dis*. 2018;66(1):149–53. [\[CrossRef\]](#)
- 60 Komorowski M, Celi LA, Badawi O, Gordon AC, Faisal AA. The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care. *Nat Med*. 2018;24(11):1716–20. [\[CrossRef\]](#)
- 61 Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. *Science*. 2019;366(6464):447–53. [\[CrossRef\]](#)
- 62 Topol EJ. Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again. New York: Basic Books; 2019.
- 63 Prentzas N, Kakas A, Pattichis CS. Explainable AI applications in the medical domain: a systematic review. *arXiv*. 2023;2308.05411. [\[CrossRef\]](#)
- 64 World Health Organization. Ethics and governance of artificial intelligence for health: WHO guidance [Internet]. Geneva: World Health Organization; 2021. [cited May 5, 2026]. Available from: <https://www.who.int/publications/item/9789240029200>