ORIGINAL RESEARCH

Integrating AI into infection control: Evaluating the accuracy and consistency of four leading platforms across three regions

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BACKGROUND: Artificial Intelligence (AI) has emerged as a valuable tool in health care, supporting diagnostics and decision making. However, integration into clinical practice presents challenges, including data quality, accessibility, and regional guideline variations. This study evaluates four major AI platforms (ChatGPT, Meta AI, Copilot, and OpenEvidence) against CDC infection control guidelines for varicella and measles across Canada, Malaysia, and the United Kingdom.

The objective was to assess the accuracy and consistency of AI responses on infection control measures compared with CDC guidelines and to evaluate how platforms handle complex scenarios.

METHODS: A comparative analysis of the four AI platforms was conducted using structured questions and clinical case scenarios on varicella and measles. Responses were evaluated for alignment with CDC guidelines. Platform accessibility was tested from Canada, Malaysia, and the United Kingdom, and regional variations were analyzed.

RESULTS: All platforms provided generally accurate information, but discrepancies were noted. ChatGPT and Meta AI mostly aligned with CDC guidelines, while OpenEvidence and Copilot omitted key epidemiological criteria. Meta AI lacked a full explanation of varicella laboratory criteria and was inaccessible in Malaysia. Regional differences in measles postexposure prophylaxis (PEP) were observed, particularly in Copilot and OpenEvidence. Response consistency varied between platforms.

CONCLUSIONS: AI platforms show promise in supporting infection control but exhibit regional variability. Continued refinement of AI tools is essential to ensure their global applicability and accuracy. Consultation with an infection prevention and control (IPAC) physician remains vital for complex cases.

KEYWORDS: artificial intelligence (AI), case definition, infection control measures, infectious period, Malaysia, measles, varicella

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HISTORIQUE : L'intelligence artificielle (IA) s'est révélée un outil précieux dans le milieu de la santé, car elle appuie les diagnostics et les processus décisionnels. Cependant, son intégration à la pratique privée comporte des défis, y compris la qualité des données, l'accessibilité et les variations aux directives régionales. La présente étude évalue quatre grandes plateformes d'IA (ChatGPT, Meta AI, Copilot et OpenEvidence) par rapport aux directives de contrôle des infections des CDC au sujet de la varicelle et de la rougeole au Canada, en Malaisie et au Royaume-Uni.

L'objectif était d'évaluer l'exactitude et l'uniformité des réponses de l'IA aux mesures de contrôle des infections par rapport aux directives des CDC et examiner comment les plateformes traitent les scénarios complexes.

MÉTHODOLOGIE : Les chercheurs ont réalisé une analyse des quatre plateformes d'IA à l'aide de questions structurées et de scénarios de cas complexes sur la varicelle et la rougeole. Ils ont évalué les réponses pour vérifier si elles étaient conformes aux directives des CDC. Ils ont testé l'accessibilité des plateformes du Canada, de la Malaisie et du Royaume-Uni et analysé les variations régionales.

RÉSULTATS : Toutes les plateformes ont généralement fourni de l'information exacte, mais des écarts ont été constatés. ChatGPT et Meta AI se conformaient le mieux aux directives des CDC, tandis qu'OpenEvidence et Copilot omettaient des critères épidémiologiques clés. Meta AI ne fournissait pas d'explication complète sur les critères de laboratoire relatifs à la varicelle et n'était pas accessible en Malaisie. Des différences régionales ont été observées relativement à la prophylaxie postexposition (PEP) de la rougeole, notamment dans Copilot et OpenEvidence. L'uniformité des réponses variait selon les plateformes.

CONCLUSIONS : Les plateformes d'IA sont prometteuses pour appuyer le contrôle des infections, mais présentent une variabilité régionale. Il est essentiel d'assurer le peaufinage continu des outils d'IA pour en garantir l'applicabilité et l'exactitude mondiales. Une consultation avec un médecin en prévention et en contrôle des infections (PCI) demeure cruciale dans les cas complexes.

MOTS-CLÉS : définition de cas, intelligence artificielle (IA), Malaisie, mesures de contrôle des infections, période infectieuse, rougeole, varicelle

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INTRODUCTION

Innovations in medical technology and the availability of point-of-care artificial intelligence (AI) tools are posed to reshape the evolution of health care delivery around the globe. Traditional workflows, which are reliant on manual processes, are resource-intensive, time-consuming, and prone to human error (1). In the field of infectious diseases, AI has addressed challenges and shown promise in several domains including diagnostics, imaging, decision making, surveillance, outbreak management, and drug discovery (2–4). When applied to infection control, AI can potentially improve accuracy and efficiency by automating critical steps such as case identification, response recommendations, and follow-up, ultimately enhancing patient outcomes.

Recent studies have explored AI's potential use in health care–associated infection (HAI) surveillance, particularly with machine learning and deep learning (5–13). Wiemken and Carrico demonstrated AI's accuracy in identifying health care-associated infections (HAIs), confirming its effectiveness for HAI surveillance (14). AI can analyze large data volumes quickly, enabling real-time predictive modeling and decision support systems, which are transforming early detection, resource allocation, and clinical outcomes (15). Pinsky et al highlighted AI's use in intensive care units to predict critical conditions by analyzing multisource patient data for real-time clinical decision support (16).

Despite this progress, the use of AI tools in infection prevention and control (IPAC) remains underexplored, particularly in the context of frontline exposure management. There are few published evaluations of general-purpose AI platforms for infection control scenarios such as postexposure prophylaxis (PEP), case definition interpretation, or outbreak containment guidance (17–21).

This study assesses the performance of four major AI platforms—ChatGPT 4.0 mini (OpenAI), Meta AI (Meta), Copilot (Microsoft), and OpenEvidence (Unite AI)—against CDC infection control benchmarks (17–25) as of December 2024. It also evaluates the accessibility and standardization of AI platforms across three regions: Canada, Malaysia, and the United Kingdom. The primary aim was to assess how accurately and consistently these platforms interpret and apply CDC infection control guidance. Our hypothesis was that although platforms would generally provide correct core recommendations, we would observe variation in completeness, regional alignment, and citation practices in addition to highlighting limitations in their use as standalone decision support tools for IPAC.

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METHODS

Study design and platform selection

A descriptive comparative analysis was conducted to evaluate the responses of four AI platforms (ChatGPT 4.0 mini, Meta AI, Copilot, and OpenEvidence) to structured questions and clinical case scenarios related to infection control measures for varicella and measles.

Scenario development

The clinical scenarios were internally developed by the IPAC team as part of resident training exercises and have not been published online. The clinical case scenarios are hypothetical and simulated and are not based on actual events or patients. All question sets are available in the supplementary appendices.

Standard of reference

To assess response accuracy, answers generated by the AI platforms were compared with the most recent guidelines and recommendations from the US Centers for Disease Control and Prevention (CDC), which were current as of December 2024. Any references cited within the responses were reviewed for their existence and relevance. Also, to simulate real-world usage, CDC guidelines or definitions were not uploaded or referenced explicitly in prompts.

CDC case definition: varicella: A confirmed case of varicella is defined by the CDC's varicella/chickenpox 2024 case definition as one that meets both clinical and laboratory criteria or by a patient presenting with a generalized vesicular rash and an epidemiologic link to another confirmed case (22).

CDC case definition: measles meta: According to the CDC's measles/rubella 2013 case definition, a confirmed case is defined by an acute febrile rash illness with either laboratory confirmation or direct epidemiologic linkage to a confirmed case (23).

CDC infectious period: The contagious period for varicella is from 1 to 2 days before the rash until all lesions have crusted. For measles, it spans from 4 days before to 4 days after the onset of the rash (24,25).

Data collection and testing procedure

To evaluate the accessibility of AI platforms and the consistency of their responses to clinical vignette scenarios, the study team (composed of members from Canada, Malaysia, and the United Kingdom) conducted a test in which all four platforms were asked a similar set of questions alongside two clinical case scenarios. The team connected to VPNs emulating geographic access relevant to each country. Additionally, it examined the consistency of answers between platforms and their sources of reference. We utilized free access accounts provided by all platforms and exclusively relied on their available free features. Data collection was conducted across three regions at different times between December 3, 2024, and December 18, 2024.

RESULTS

Accuracy

The accuracy of all four AI platforms was assessed using data collected from Canada, which served as the primary study site. Responses from all AI platforms were collected from December 3, 2024, to December 18, 2024, prior to being analyzed.

Consistency of AI responses across regions

The consistency of responses from all four AI platforms across Canada, Malaysia, and the United Kingdom regarding case definitions and case scenarios were also evaluated. A broader comparison of platform-level accuracy, strength, and limitations is presented Table 1. This comparison offers a consolidated view of each platform's performance against CDC guidance across various scenarios, combining both regional consistency and overall agreement with guideline-based recommendations.

ChatGPT

ChatGPT showed inconsistencies in case definitions for varicella and measles across Canada, Malaysia, and the United Kingdom. In Canada and Malaysia, both clinical and laboratory confirmation, along with epidemiologic linkage, were required for a confirmed case, while in the United Kingdom, only clinical and laboratory confirmation was needed. Despite this, ChatGPT provided consistent responses to case scenarios across all regions but did not include reference links for verification.

Meta AI

Meta AI was not yet accessible in Malaysia during this study period, thus it was only evaluated in Canada and the United Kingdom. Meta AI accessed in Canada and the United Kingdom provided consistent responses on case definitions. However, it recommended additional immunoglobulin for an 8-year-old child receiving IVIg in Canada, but not in the United Kingdom. No reference links were provided for the measles case scenario, making it unclear if responses followed specific guidelines as shown in Figure 1.

Table 1: Variations of responses from all four platforms

Platform	Overall agreement with CDC guidance	Limitations	Strengths
ChatGPT	High alignment in most clinical scenarios (eg, infectious period, vaccinated PEP for pregnant individuals). Consistent across countries for measles scenarios.	Did not provide case definitions. Some variability in varicella acyclovir duration. Reported IVIg timing correctly, but responses lacked references.	Strong overall consistency; safest for measles case scenarios across regions.
Meta AI	Moderate alignment. Aligned on infectious periods, basic varicella management, and PEP for pregnant individuals.	Incorrect IVIg timing (<72 h) for measles PEP. Did not always match CDC in measles scenarios. Did not cite references.	Provided case definitions. Often gave clear-cut answers where consistent.
Copilot	Lower alignment compared with others. Provided inconsistent responses for newborn varicella, measles child scenarios, and HIV cases.	Added antivirals inappropriately to varicella pregnancy management. Outlier recommending MMR vaccination in an HIV patient. Did not align across countries for measles.	Cited references. Provided case definitions.
OpenEvidence	Highest overall alignment with CDC guidance. Generally correct on infectious periods, varicella PEP, and measles management.	Gaps in newborn varicella management (monitoring only). Did not align across countries for measles. Some answers lacked details (eg, acyclovir duration).	Cited references. Provided case definitions. Strong platform-level consistency for most scenarios.

CDC = US Centers for Disease Control and Prevention; IVIg = Intravenous immunoglobulin; MMR = Measles, mumps, rubella; PEP = Postexposure prophylaxis

Copilot

Copilot was consistent in its responses for the case definitions of varicella and measles across all regions as well as in the varicella case scenario. However, inconsistencies were observed in Copilot's responses for the measles case scenario. For a 6-month-old immunocompetent infant exposed to measles, Copilot in Canada and Malaysia indicated that no PEP was required. In contrast, the UK version recommended IVIg, referencing a US-based source (26) rather than local UK guidelines. For an 8-year-old child receiving regular monthly IVIg, Copilot in Canada and Malaysia recommended PEP, while Copilot in the United Kingdom did not recommend it. Although all three versions referenced US-based sources, the UK version cited a different source compared with those used in Canada and Malaysia as shown in Figure 2.

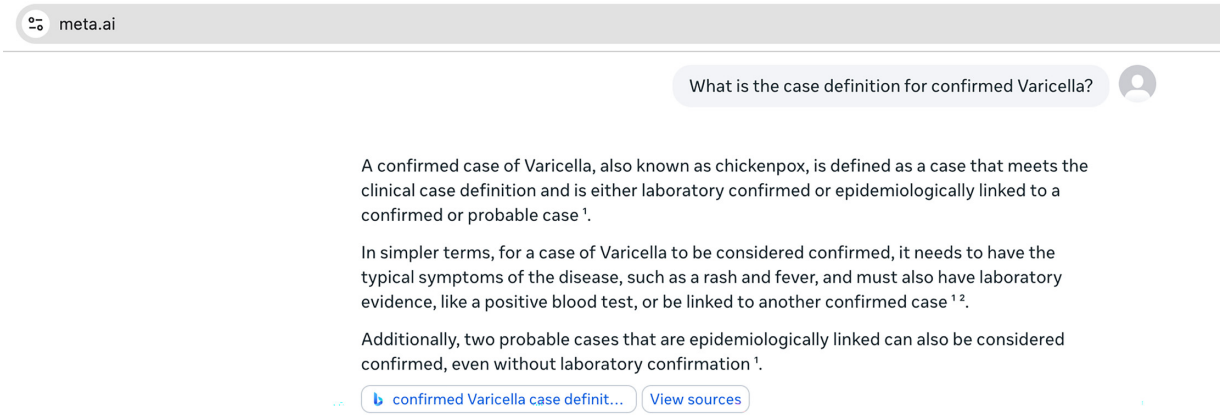

Figure 1: Responses from Meta AI, as accessed in Canada, dated December 3, 2024

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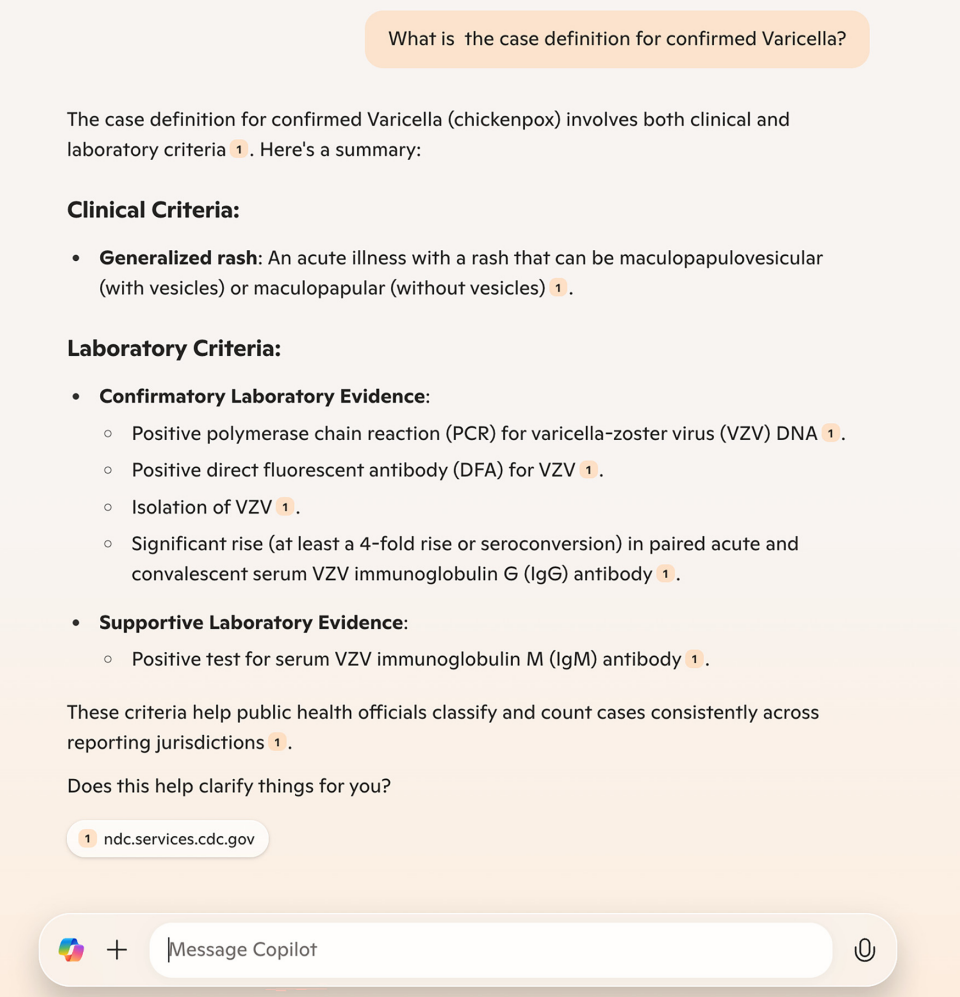

Figure 2: Responses from Copilot, as accessed in Canada, dated December 3, 2024

OpenEvidence

OpenEvidence provided consistent case definitions and varicella responses but varied in the measles case scenario. For a 6-month-old infant, OpenEvidence recommended the MMR vaccine in Canada and Malaysia, while the UK version recommended immunoglobulin, with different source citations. Both options are valid, depending on availability and circumstances.

DISCUSSION

The study evaluated the performance and consistency of four publicly accessible AI platforms including ChatGPT 4.0 mini, Meta AI, Copilot, and OpenEvidence, which provided infection control recommendations for varicella and measles exposures. Using CDC guidelines as the reference standard, we assessed both the accuracy of the platforms' responses and their consistency across regional contexts including Canada, Malaysia, and United Kingdom. The platforms generally delivered case definitions for varicella and measles that aligned with CDC guidelines. ChatGPT and Meta AI demonstrated the closest adherence, incorporating essential elements of the case definitions, which suggest potential utility in helping integrate diagnostic criteria into infection control workflows. However, Copilot and OpenEvidence occasionally omitted key features such as epidemiologic criteria for varicella, raising concern about incomplete or inaccurate guidance in resource limited setting with limited access to laboratory testing.

Meta AI's simplified version of varicella's case definition may support basic triage but falls short for complex cases requiring comprehensive diagnostic precision, as summarized in Table 1. All four platforms consistently reported accurate infectious periods for both diseases, reinforcing their potential value in automating time-sensitive infection control tasks. For varicella treatment, ChatGPT and Meta

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AI recommended oral acyclovir but offered slightly different treatment durations, while Copilot omitted dosage, and OpenEvidence did not address duration. These differences point to variations in completeness that could affect decision making. Some variations in the responses were minor, such as missing citations or imprecise phrasing, which had little impact on clinical decision making. Others were more clinically relevant such as omitting prophylaxis entirely or recommending the wrong approach for high-risk patients, which could pose safety concerns. In addition, discrepancies were more pronounced when platforms addressed PEP, especially in vulnerable populations. For instance, Copilot did not cite any reference for the PEP management of a 6-month-old child who was exposed to measles and provided limited guidance for a child with HIV and a low CD4 count; however, the Minnesota Department of Health reference was cited for the HIV case (26), though it lacked specific guidance. Meta AI also deviated from CDC recommendations by suggesting a 72-hour window for immunoglobulin administration compared with the CDC's 6-day recommendation (20). These examples highlight the need for AI platforms to remain aligned with current, evidence-based guidelines, especially when dealing with paediatric or immunocompromised populations.

The inability of platforms to reference guidelines consistently or provide detailed dosing information limits their role in complex infection control decisions. In scenarios such as measles exposure in children receiving regular IVIg, the lack of contextual clarification (eg, when the last IVIg dose was administered) illustrates a broader limitation: These AI platforms cannot ask follow-up questions. This restricts their ability to deliver nuanced recommendations based on patient-specific timelines, reinforcing the need for human oversight in cases requiring clinical judgment.

Regional variation further affected the reliability of AI-generated responses. ChatGPT included epidemiologic links and both clinical and laboratory confirmation in its Canadian and Malaysian responses but omitted these in the United Kingdom, despite using the same prompt. Meta AI displayed inconsistency by recommending PEP for an 8-year-old child receiving regular IVIg in Canada, but not in the United Kingdom. The absence of a citation in these responses made it difficult to discern whether differences were based on local guidelines or simply variability in the platform's output. Copilot recommended immunoglobulin for the same 6-month-old measles exposure case in the United Kingdom using a reference from the Mid-Michigan District Health Department, while recommending no PEP for similar cases in Canada and Malaysia (27). Although OpenEvidence showed the most consistent alignment with CDC recommendations, its responses also varied slightly by region, which may reflect differences in the training data or in the prioritization of guidelines sources across jurisdictions.

Several limitations should be noted. A key limitation of this study is the lack of a formal quantitative assessment of accuracy. We relied on dichotomized outcomes (agreement versus disagreement with CDC guidance), which required readers to interpret accuracy by reviewing tables rather than by a calculated score. This differs from prior studies (eg, Abosi et al, 2024) that applied structed accuracy metrics (28). Incorporating such quantitative measures in future work would allow more precise benchmarking and facilitate comparisons across studies. We also observed regional variability in AI responses. This may reflect how models prioritize information, including location-based defaults or source availability. Importantly, because the AI platforms were not explicitly promoted to use CDC guidelines, some outputs may have drawn on non-US sources, introducing variability or regional bias. In real-world setting, this could be beneficial or problematic depending on local applicability, underscoring the importance of source transparency. Measles and varicella were selected as test cases because they remain among the most transmissible vaccine-preventable infection prevention teams. Both require urgent assessment and postexposure management, and guidance is well established, making them appropriate conditions against which to benchmark AI performance.

Other methodological limitation should also be acknowledged. Only four AI platforms were evaluated, so the findings may not represent the full range of tools available. Moreover, AI outputs are dynamic and change as models are updated, requiring repeated assessment over time. Each platform was tested using a single, static prompt for each scenario, without follow-up or re-prompting. In practice, users often interact with these systems more dynamically, which might improve accuracy and completeness. We also did not upload guidelines into the platform prior to posing questions, a step that could increase alignment with regional protocols. Finally, although our focus on varicella and measles was deliberate given their relevance to IPAC, it limits generalizability to other pathogens with more complex diagnostics or management.

Our findings complement prior work while highlighting notable differences in methodology and outcome. For example, Abosi et al assessed four large language models using 31 real-world clinical infection prevention questions and reported a 98.9% accuracy rate with 94.6% completeness (28). Their evaluation involved Likert-scale scoring by interaction with the models. In contrast, our study used static prompts and simulated case scenarios focusing specifically on varicella and measles exposure. This

design revealed greater variability, particularly in completeness and regional consistency. Similarly, Wiemken and Carrico evaluated AI performance in the context of health care–associated infections using National Healthcare Safety Network (NHSN) training materials (14), while our work addressed community-acquired, vaccine-preventable infections and real-world public-facing platforms.

CONCLUSION

The evaluated AI platforms demonstrated varying levels of accuracy and consistency in managing varicella and measles exposures. Although platforms like ChatGPT and Meta AI showed relatively strong performance, inconsistencies across regions and limitations in providing detailed, guideline-based responses highlight the need for ongoing development and caution in clinical use. These platforms hold promise as supportive tools, but are not yet mature. Health care professionals, especially those in IPAC, should remain central in guiding decisions related to infectious disease exposures, particularly in cases that require individualized assessment or interpretation of evolving guidelines. Consultation with an IPAC physician remains essential when dealing with complex infection control issues.

ACKNOWLEDGEMENTS: The authors would like to thank Dr Dominik Mertz and Dr Sarah Khan for their clinical case scenario ideas.

CONTRIBUTORS: Conceptualization, J Julkipli, J Delport, Al Mutawa; Methodology, J Julkipli, F Al Mutawa; Investigation, J Julkipli; Data Curation, J Julkipli, Y Saw, U Zainulabid; Writing – Original Draft, J Julkipli, A Alanazi, A Alanazi; Writing – Review and Editing, J Julkipli, A Alanazi, J Delport, R Gupta, M Silverman, MR Rahimi Shahmirzadi, S Elsayed, F Al Mutawa, A Alanazi.

ETHICS APPROVAL STATEMENT: This study did not involve human participants or the use of identifiable personal data. Therefore, institutional ethics approval was not required.

INFORMED CONSENT: N/A

REGISTRY AND THE REGISTRATION NO. OF THE STUDY/TRIAL: N/A

DATA ACCESSIBILITY: All data, including clinical scenarios and prompts, are available in the supplementary appendices. Additional data can be provided upon request to the corresponding author.

FUNDING: This study was not funded by any organization.

DISCLOSURES: The authors declare no conflicts of interest.

PEER REVIEW: This article has been peer reviewed.

ANIMAL STUDIES: N/A

REFERENCES

1. Alowais SA, Alghamdi SS, Alsuhebany N, et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Med Educ. 2023;23(1):689. https://doi.org/10.1186/s12909-023-04698-z. Medline: 37740191
2. Agrebi S, Larbi A. Chapter 18—Use of artificial intelligence in infectious diseases. In: Barh D, eds. Artificial Intelligence in Precision Health. Academic Press; 2020: 415–38. ISBN 978-0-12-817133-2.
3. Theodosiou AA, Read RC. Artificial intelligence, machine learning and deep learning: potential resources for the infection clinician. J Infect. 2023;87(4):287–94. https://doi.org/10.1016/j.jinf.2023.07.006. Medline: 37468046
4. Sarantopoulos A, Mastori Kourmpani C, Yokarasa AL, et al. Artificial intelligence in infectious disease clinical practice: an overview of gaps, opportunities, and limitations. Trop Med Infect Dis. 2024;9(10):228. https://doi.org/10.3390/tropicalmed9100228. Medline: 39453255
5. Yang L, Lu S, Zhou L. The implications of artificial intelligence on infection prevention and control: current progress and future perspectives. China CDC Wkly. 2024;6(35):901–4. https://doi.org/10.46234/ccdcw2024.192. Medline: 39233995
6. Goh KH, Wang L, Yeow AYK, et al. Artificial intelligence in sepsis early prediction and diagnosis using unstructured data in healthcare. Nat Commun. 2021;12(1):711. https://doi.org/10.1038/s41467-021-20910-4. Medline: 33514699
7. Bhargava A, López-Espina C, Schmalz L, et al. FDA-authorized AI/ML tool for sepsis prediction: development and validation. NEJM AI. 2024;1(12). https://doi.org/10.1056/AIoa2400867
8. Dos Santos RP, Silva D, Menezes A. Automated healthcare-associated infection surveillance using an artificial intelligence algorithm. Infect Prev Pract. 2021;3(3):100167. https://doi.org/10.1016/j.infpip.2021.100167. Medline: 34471868
9. Barchitta M, Maugeri A, Favara G, et al. A machine learning approach to predict healthcare-associated infections at intensive care unit admission: findings from the SPIN-UTI project. J Hosp Infect. 2021;112:77–86. https://doi.org/10.1016/j.jhin.2021.02.025. Medline: 33676936

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10. Beeler C, Dbeibo L, Kelley K, et al. Assessing patient risk of central line–associated bacteraemia via machine learning. Am J Infect Control. 2018;46(9):986–91. https://doi.org/10.1016/j.ajic.2018.02.021. Medline: 29661634
11. Liao YH, Wang ZC, Zhang FG, et al. Machine learning methods applied to predict ventilator-associated pneumonia with *Pseudomonas aeruginosa* infection via sensor array of electronic nose in intensive care unit. Sensors (Basel). 2019;19(8):1866. https://doi.org/10.3390/s19081866. Medline: 31003541
12. Montella E, Ferraro A, Sperlì G, Triassi M, Santini S, Improta G. Predictive analysis of healthcare-associated bloodstream infections in the neonatal intensive care unit using artificial intelligence: a single center study. Int J Environ Res Public Health. 2022;19(5):2498. https://doi.org/10.3390/ijerph19052498. Medline: 35270190
13. Scardoni A, Balzarini F, Signorelli C, et al. Artificial intelligence–based tools to control healthcare-associated infections: a systematic review of the literature. J Infect Public Health. 2020;13(8):1061–77. https://doi.org/10.1016/j.jiph.2020.06.006. Medline: 32561275
14. Wiemken TL, Carrico RM. Assisting the infection preventionist: use of artificial intelligence for healthcare-associated infection surveillance. Am J Infect Control. 2024;52(6):625–9. https://doi.org/10.1016/j.ajic.2024.02.007. Medline: 38483430
15. Dixon D, Sattar H, Moros N, et al. Unveiling the influence of AI predictive analytics on patient outcomes: a comprehensive narrative review. Cureus. 2024;16(5):e59954. https://doi.org/10.7759/cureus.59954. Medline: 38854327
16. Pinsky MR, Dubrawski A, Clermont G. Intelligent clinical decision support. Sensors (Basel). 2022;22(4):1408. https://doi.org/10.3390/s22041408. Medline: 35214310
17. Centers for Disease Control and Prevention (CDC). Clinical guidance for healthcare providers: chickenpox (varicella). Last reviewed April 13, 2020. https://www.cdc.gov/chickenpox/hcp/clinical-guidance/index.html
18. Centers for Disease Control and Prevention (CDC). Chickenpox (varicella). CDC Yellow Book: Health Information for International Travel. https://www.cdc.gov/chickenpox/hcp/clinical-overview/
19. Centers for Disease Control and Prevention (CDC). Contraindications to breastfeeding or feeding expressed breast milk to infants. Last modified August 21, 2023. https://www.cdc.gov/breastfeeding-special-circumstances/hcp/contraindications/index.html
20. Centers for Disease Control and Prevention (CDC). Updated recommendations for use of VariZIG—United States, 2013. MMWR Morb Mortal Weekly Rep. 2013;62(28):574–6. https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6228a4.htm. Medline: 23863705
21. Centers for Disease Control and Prevention (CDC). Measles, rubella, congenital rubella syndrome, and mumps—United States, 2005–2014. MMWR Recomm Rep. 2013;62(4):119. https://www.cdc.gov/mmwr/preview/mmwrhtml/rr6204a1.htm
22. Centers for Disease Control and Prevention (CDC). Varicella/chickenpox 2024 case definition. 2024. https://ndc.services.cdc.gov/case-definitions/varicella-2024/
23. Centers for Disease Control and Prevention (CDC). Measles/rubella 2013 case definition. 2013. https://ndc.services.cdc.gov/case-definitions/measles-2013/
24. Centers for Disease Control and Prevention (CDC). Chickenpox (varicella): clinical overview of chickenpox (varicella). https://www.cdc.gov/chickenpox/hcp/clinical-overview/index.html
25. Centers for Disease Control and Prevention (CDC). Measles (rubeola): clinical overview of measles. https://www.cdc.gov/measles/hcp/clinical-overview/index.html
26. Minnesota Department of Health. Measles post-exposure prophylaxis (PEP) for non symptomatic susceptible contacts. Last modified July 15, 2025. https://www.health.state.mn.us/diseases/measles/hcp/measlespep.pdf
27. Mid-Michigan District Health Department (MMDHD). Measles post-exposure prophylaxis recommendations for non-symptomatic susceptible contacts. Last modified April 17, 2019. https://www.health.state.mn.us/diseases/measles/hcp/measlespep.pdf
28. Abosi OJ, Kobayashi T, Ross N, et al. A head-to-head comparison of the accuracy of commercially available large language models for infection prevention and control inquiries. Infect Control Hosp Epidemiol. 2024;46(3):1–3. https://doi.org/10.1017/ice.2024.205. Medline: 39664019