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Artificial Intelligence for Infection Surveillance: Improving Early Detection of Healthcare-Associated Infections

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Abstract

Healthcare-associated infections (HAIs) remain a leading cause of preventable morbidity, mortality, and excess healthcare spending worldwide, and traditional manual surveillance is labor-intensive, inconsistent, and often too slow to support timely intervention. Artificial intelligence (AI) including machine learning (ML), natural language processing (NLP), and hybrid rule-based/statistical systems have emerged as a candidate solution for automating and accelerating HAI detection using data already captured in electronic health records (EHRs). This narrative review synthesizes recent evidence on AI-driven infection surveillance across major HAI categories, including sepsis, surgical site infections (SSIs), device-associated infections, and outbreak-level public health surveillance. Across studies, AI-augmented surveillance systems have demonstrated the ability to match or exceed the sensitivity of manual chart review while substantially reducing reviewer workload, and NLP applied to unstructured clinical notes has repeatedly improved detection accuracy relative to structured data alone. However, performance is highly heterogeneous across institutions, infection types, and algorithms, and several widely deployed proprietary tools, most notably early sepsis early-warning systems have shown poor external validity, low positive predictive value, and a tendency to generate clinically disruptive alert fatigue. Persistent barriers include limited model portability across health systems, opaque ("black box") decision logic, inconsistent reference-standard definitions, and the absence of standardized regulatory or reporting frameworks for surveillance-oriented AI. We conclude that AI-driven infection surveillance can meaningfully augment infection prevention programs when rigorously externally validated, transparently reported, and implemented as a human-in-the-loop workflow rather than a fully autonomous decision system, and we outline priority areas for future research and implementation science.

Keywords: *Artificial intelligence; machine learning; natural language processing; healthcare-associated infections; infection surveillance; sepsis; electronic health records; patient safety*

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1. Introduction

Healthcare-associated infections are infections acquired during the receipt of medical care that were not present or incubating at admission, and they remain one of the most common adverse events in modern healthcare systems [3]. In the United States, national point-prevalence data collected by the Centers for Disease Control and Prevention (CDC) indicate that on any given day roughly 1 in 31 hospital patients has at least one HAI, with about half of hospitalized patients receiving an antimicrobial agent [10]. A companion analysis comparing prevalence surveys conducted in 2023 and 2015 found that overall, HAI burden had declined but remained substantial, with an estimated 518,000 HAIs occurring in United States acute care hospitals in 2023 and patients roughly 27% less likely to have an HAI than in 2015 [9]. Outside the United States, the second European Point Prevalence Survey estimated approximately 8.9 million HAI episodes affecting 3.8 million patients across European healthcare facilities, underscoring that this is a global patient-safety problem rather than a nation-specific one [19].

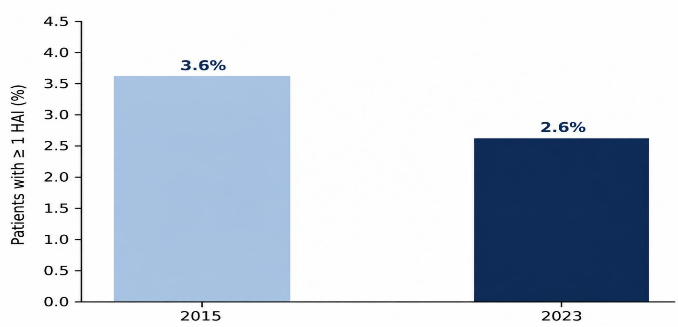

Figure 1. Prevalence of healthcare-associated infections (HAIs) among hospitalized patients in the United States, 2015 versus 2023.

The figure compares the estimated point prevalence of patients with at least one healthcare-associated infection (HAI) during national U.S. hospital prevalence surveys. The prevalence declined from 3.6% in 2015 to 2.6% in 2023, representing an approximate 27% relative reduction in the proportion of hospitalized patients affected by HAI. This decline reflects continued improvements in infection prevention and control practices, including enhanced surveillance, implementation of evidence-based prevention bundles, antimicrobial stewardship, and strengthened quality improvement initiatives across U.S. healthcare facilities. The findings demonstrate substantial national progress in reducing the burden of HAIs while emphasizing the ongoing need for continuous surveillance and prevention efforts. Source: CDC Emerging Infections Program Hospital Prevalence Survey.

Surveillance the systematic, ongoing collection, analysis, and interpretation of infection data is the foundation on which infection prevention and control (IPC) programs are built, because it identifies where transmission or risk is occurring and whether interventions are working [6]. Conventional HAI surveillance, however, still relies heavily on manual chart abstraction by infection preventionists applying standardized surveillance definitions (such as those of the National Healthcare Safety Network, NHSN), a process widely described as labor-intensive, subject to interobserver variability, and prone to underreporting [6], [25]. As EHR adoption has become nearly universal, attention has shifted toward using the structured and unstructured data already generated during clinical care vital signs, laboratory results, medication orders, and free-text clinical notes to build automated or semi-automated surveillance systems capable of flagging likely HAIs for confirmation or even predicting infections before they are clinically apparent [5].

Artificial intelligence, broadly encompassing machine learning and natural language processing, offers a plausible technical path toward this goal because it can integrate heterogeneous, high-volume data streams in ways that exceed the practical capacity of manual review [2], [7]. This review synthesizes recent peer-reviewed literature on AI-driven approaches to HAI surveillance, describes the principal application areas and the strength of the supporting evidence, and critically examines the implementation barriers that have limited the translation of promising model performance into reliable, generalizable clinical impact.

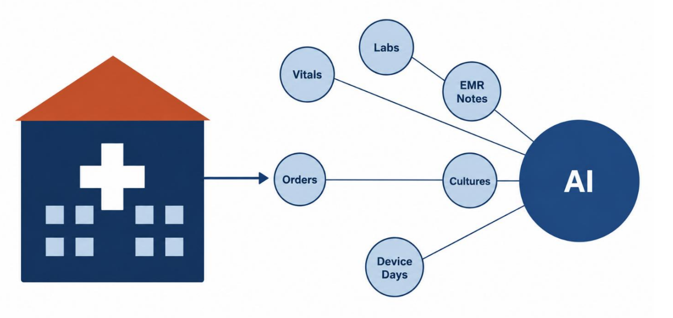

Figure 2. Hospital data streams feeding an artificial intelligence (AI) surveillance system for infection detection.

The diagram illustrates the integration of multiple clinical data sources into an AI-powered infection surveillance platform. Structured and unstructured hospital data including vital signs, laboratory results, medication and clinical orders, electronic medical record (EMR) notes, microbiology culture results, and device utilization (device days) are aggregated and analyzed by AI algorithms to identify patients at increased risk of healthcare-associated infections (HAIs). By continuously processing diverse clinical information in near real time, the AI surveillance layer supports early case detection, risk stratification, and timely infection prevention interventions, thereby enhancing surveillance efficiency, clinical decision-making, and patient safety.

2. Methods

This manuscript is structured as a narrative synthesis rather than a formal systematic review. Sources were identified through targeted searches of the biomedical and health-informatics literature (PubMed/PMC, ScienceDirect, and major journal sites including the New England Journal of Medicine, NEJM AI, and npj Digital Medicine) using combinations of the terms "artificial intelligence," "machine learning," "natural language processing," "healthcare-associated infection," "infection surveillance," and "sepsis prediction," supplemented by CDC and ECDC surveillance reports. Priority was given to systematic reviews, multi-site external validation studies, and national surveillance reports published within the past several years, alongside seminal earlier studies where they remain the primary evidence for a given tool (e.g., early sepsis early-warning systems). Given the narrative format, this review does not report a formal risk-of-bias assessment or PRISMA flow; readers seeking a fully systematic, quality-appraised synthesis are referred to the systematic reviews cited throughout, several of which applied TRIPOD or AMSTAR 2 criteria to the primary literature.

3. AI Approaches Applied to Infection Surveillance

3.1 Machine learning and predictive analytics

Supervised ML models logistic regression, random forests, gradient-boosted trees, and increasingly deep learning architectures such as recurrent neural networks are trained on structured EHR variables (vital signs, laboratory trends, medication and device orders, comorbidity codes) to classify patients as infected or at risk of infection, or to predict infection onset ahead of clinical recognition [1], [4]. These models underpin most contemporary sepsis early-warning systems and a growing number of SSI and device-associated infection prediction tools.

3.2 Natural language processing of clinical text

A substantial share of clinically relevant infection information wound descriptions, culture interpretations, radiology impressions, and clinician reasoning exists only in unstructured free text. NLP techniques, ranging from rule-based keyword/negation extraction to fine-tuned language models, are used to extract this information and combine it with structured data [25], [28]. Multiple studies report that incorporating NLP-derived features measurably improves detection sensitivity relative to structured data alone, particularly for SSIs, where key evidence of infection (purulent drainage, wound reopening, clinician diagnosis) is frequently documented only in narrative notes [16].

3.3 Automated and semi-automated surveillance systems

Rather than fully replacing human review, many deployed systems function as semi-automated surveillance: an algorithm screens the entire patient population and returns a much smaller, enriched subset for manual confirmation by an infection preventionist, reducing chart-review workload while preserving human oversight of the final HAI determination [16], [26]. This human-in-the-loop design has emerged as the dominant implementation pattern in the recent literature, reflecting both accuracy limitations of fully automated classification and the medicolegal/reporting requirements attached to official HAI determinations.

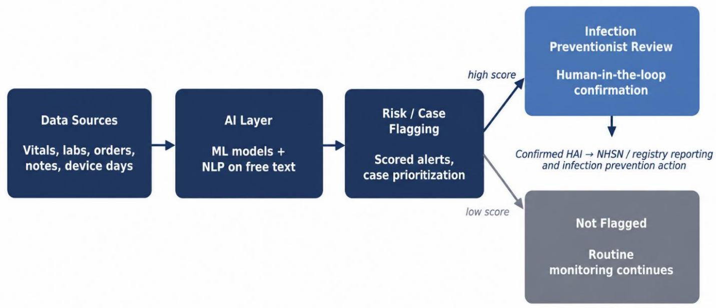

Figure3. Human-in-the-loop artificial intelligence (AI) surveillance workflow for healthcare-associated infection (HAI) detection.

4. Applications by Infection Type

4.1 Sepsis

Sepsis prediction has attracted the most sustained AI research investment of any HAI-adjacent application, beginning with early tools such as the Targeted Real-Time Early Warning Score (TREWScore) and continuing through numerous commercial and academic early-warning systems [3]. A recent narrative synthesis reported that AI-based sepsis prediction models achieve moderate-to-very-good discrimination (accuracy roughly 61%–99% across heterogeneous studies) and can flag patients anywhere from 0 to 40 hours before clinically recognized onset, though study settings, populations, and sepsis definitions vary considerably [4]. Performance in real-world, external deployment has often been substantially weaker than in development cohorts, a pattern discussed further in Section 6.

4.2 Surgical site infections

SSI surveillance has become one of the most extensively studied AI/NLP use cases because SSIs are common, costly, and heavily underreported by administrative data alone. A rules-based NLP system for postoperative note review achieved internal-validation sensitivity of 92.5%, specificity of 88.5%, and an AUC of 0.905, though performance fell to 78.2% sensitivity and an AUC of 0.851 on external validation at a second health system, with the largest drops occurring for less common procedure types such as vascular surgery [17]. A separate hybrid ML/rule-based semi-automated system reported that pooled sensitivity for text-inclusive models (0.83) was substantially higher than for structured-data-only models (0.56) in a systematic review of electronically assisted SSI surveillance tools, while noting wide heterogeneity across studies (sensitivity 0.02–1.0, specificity 0.59–1.0) [16]. Other groups combining structured EHR data with document- and keyword-level NLP features report more modest but highly specific performance (sensitivity 0.58, specificity 0.97, positive predictive value 0.54), reflecting a common trade-off in this literature between sensitivity and workload-reducing specificity [15]. Feature-importance approaches such as SHAP have also been applied to XGBoost-based SSI models to make individual predictions more interpretable to infection prevention staff [18].

4.3 Device-associated infections and Clostridioides difficile

Beyond sepsis and SSI, AI and NLP methods have been applied to central line-associated bloodstream infections, catheter-associated urinary tract infections, ventilator-associated pneumonia, and C. difficile infection, generally using structured EHR triggers (device days, culture orders, laboratory results) supplemented by NLP-extracted clinical documentation. Reported sensitivity and specificity for these electronically assisted surveillance systems range widely (approximately 54%–100% and 64%–100%, respectively) depending on infection type, reference standard, and health-system data quality [4]. Models for SSI and urinary tract infection detection specifically have frequently achieved AUC values above 0.80 in integrative reviews of the predictive-analytics literature [1].

4.4 Outbreak detection and public-health-level surveillance

At the population level, AI systems that integrate EHR data with non-clinical sources travel records, social media, spatiotemporal and wastewater data, and environmental measurements have been used to detect and forecast infectious disease outbreaks earlier than traditional public health reporting channels allow, with demonstrated value for diseases such as COVID-19, influenza, and dengue [5], [8]. These systems address a structurally different problem than institutional HAI surveillance (population-level outbreak signal versus individual-patient infection detection) but rely on conceptually similar AI methods and share many of the same data-quality and trust challenges.

5. Performance Evidence and Clinical Impact

Table 1 summarizes reported diagnostic performance for the AI and NLP surveillance systems discussed in Section 4, drawn directly from the cited primary studies and systematic reviews. Figure 2 plots sensitivity and specificity for the subset of systems reporting both metrics.

System / Model	Infection Type	Data Used	Sensitivity	Specificity	Other Metrics	Ref.
Epic Sepsis Model (academic health system validation)	Sepsis	Structured EHR	NR	NR	AUC 0.63	11
Epic Sepsis Model v1 (2 county EDs)	Sepsis	Structured EHR	14.7%	95.3%	PPV 7.6%; NPV 97.7%; median lead time ~0 min	12
SepsisWatch (recurrent neural network)	Sepsis	Structured EHR	Site-dependent	Site-dependent	Performance degraded across external sites (portability limited)	14
FDA-authorized AI/ML sepsis prediction tool	Sepsis	Structured EHR	Reported in FDA submission	Reported in FDA submission	Completed formal development/validation pathway	13
Random Forest + NLP document-level features	Surgical site infection	Structured + NLP	58%	97%	PPV 54%; NPV 98%; F0.5 0.52	15
EasyCIE-SSI – internal validation	Surgical site infection	NLP (clinical notes)	92.5%	88.5%	AUC 0.905	17
EasyCIE-SSI – external validation	Surgical site infection	NLP (clinical notes)	78.2%	92.2%	AUC 0.851 (range 0.721–0.927 by procedure)	17
Text-inclusive models, pooled estimate	Surgical site infection	Structured + NLP	83% (95% CI 78–87%)	NR	Systematic review pooled estimate	16
Structured-data-only models, pooled estimate	Surgical site infection	Structured only	56% (95% CI 43–69%)	NR	Systematic review pooled estimate	16
Electronically assisted SSI surveillance, full range	Surgical site infection	Mixed	2–100%	59–100%	Wide heterogeneity across included studies	16
Automated device-associated HAI surveillance, range	CLABSI, CAUTI, VAP, C. difficile	Structured EHR + NLP	54.2–100%	63.5–100%	Range across infection types and algorithms	4
SSI / UTI predictive models, integrative review	Surgical site infection, UTI	Mixed	—	—	AUC commonly >0.80	1
NLP + XGBoost hip-replacement SSI surveillance	Surgical site infection	Structured + NLP + SHAP	—	—	SHAP-based feature interpretability	18

Table 1. Reported diagnostic performance of selected AI- and NLP-based infection surveillance systems. NR = not reported in the cited source; AUC = area under the receiver-operating-characteristic curve; PPV/NPV = positive/negative predictive value; CI = confidence interval. Values are taken directly from the cited primary studies and systematic reviews and are not independently pooled or re-analyzed here.

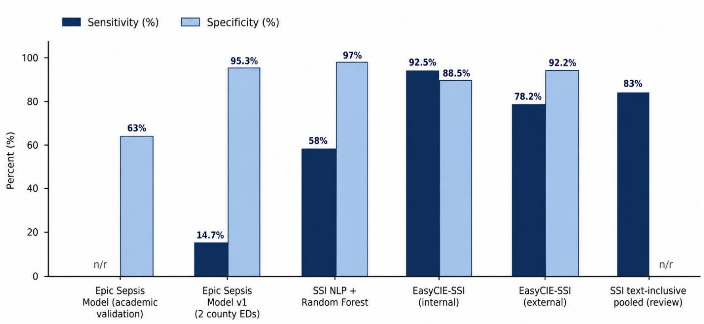

Figure 4. Reported sensitivity and specificity of selected artificial intelligence (AI) and natural language processing (NLP)-based surveillance systems for sepsis and surgical site infection (SSI).

The figure compares the reported diagnostic performance of representative AI/NLP surveillance models using sensitivity and specificity as primary evaluation metrics. EasyCIE-SSI demonstrated the highest balanced performance, with an internal validation sensitivity of 92.5% and specificity of 88.5%, while external validation reported 78.2% sensitivity and 92.2% specificity. The SSI NLP + Random Forest model achieved 58% sensitivity and 97% specificity. Epic Sepsis Model performance varied considerably across studies, with reported specificity ranging from 63% to 95.3% and sensitivity from 14.7% to values not reported. A pooled review of SSI text-inclusive surveillance systems reported an overall sensitivity of 83%, although specificity was not reported. Abbreviation: n/r, not reported.

Taken together, literature supports several consistent patterns. First, incorporating unstructured clinical text via NLP reliably improves sensitivity relative to structured-data-only models across infection types [16], [25]. Second, reported performance is highly heterogeneous, driven by differences in reference-standard definitions, patient case-mix, and institutional documentation practices, making single point estimates of "AI accuracy" for HAI surveillance potentially misleading [4], [16]. Third, semi-automated, human-in-the-loop designs that use AI to prioritize cases for manual review rather than to make autonomous HAI determinations have shown the most consistent evidence of workload reduction with preserved sensitivity [26]. Fourth, external validation at sites other than the development institution frequently reveals meaningful performance degradation, which is discussed in detail below [17], [24].

6. Challenges and Limitations

6.1 Model portability and external validity

A recurring finding across this literature is that models developed and validated at a single institution do not automatically generalize to other health systems, EHR platforms, or patient populations. A multi-site external validation of the RNN-based SepsisWatch model highlighted portability as a central obstacle to scaling ML-based sepsis detection because of variability in patient populations and care-delivery processes across sites [14]. Similarly, an NLP-based SSI surveillance tool that performed strongly at its development institution showed a statistically significant drop in sensitivity on external validation, with the largest declines for less common procedure types [17].

6.2 Alert fatigue and clinical workflow disruption

The most cautionary evidence in this field comes from external, independent evaluations of the widely deployed Epic Sepsis Model (ESM). An external validation at an academic health system found the ESM's area under the receiver-operating-characteristic curve was only 0.63, that it identified only 7% of sepsis patients who had not received timely antibiotics, and that it missed 67% of confirmed sepsis cases despite generating alerts on 18% of all hospitalized patients a substantial alert-fatigue burden for clinical staff for comparatively little diagnostic benefit [11]. A more recent evaluation of a newer version of the same tool at two county emergency departments found a sensitivity of only 14.7%, specificity of 95.3%, positive predictive value of 7.6%, and a median alert lead time of essentially zero minutes relative to clinical sepsis recognition, leading the study authors to conclude the tool added little diagnostic assistance beyond existing clinical practice [12]. These findings, alongside separate reports that the same system's alert volume rose sharply during the COVID-19 pandemic, illustrate how poorly calibrated early-warning tools can create clinically disruptive alert fatigue rather than genuine early-detection benefit [12].

6.3 Explainability, bias, and clinician trust

Many high-performing AI models, particularly deep-learning architectures, function as "black boxes" whose reasoning is not transparent to end users, which have been repeatedly identified as a barrier to clinician trust and adoption in both HAI surveillance and broader infectious-disease early-warning applications [5], [8]. Explainability techniques such as SHAP feature attribution are increasingly used to partially address this gap by surfacing which variables drove an individual prediction [18]. Because AI models learn from historical documentation and staffing patterns, they are also susceptible to reproducing biases and data-quality gaps present in the underlying EHR data, including incomplete or inconsistent nursing and physician documentation across shifts, sites, and patient subgroups an issue several reviews flag as understudied relative to model discrimination performance [2], [7].

6.4 Reference standards and regulatory/implementation barriers

Because manual surveillance definitions themselves involve subjective clinical judgment, the "ground truth" against which AI systems are validated is imperfect and varies across studies, contributing to the wide performance ranges reported for electronically assisted SSI surveillance (sensitivity 0.02–1.0, specificity 0.59–1.0 across the reviewed literature) [16]. Real-world implementation of AI-supported HAI surveillance and prediction systems in routine daily practice also remains uncommon relative to the volume of published model-development studies, reflecting gaps in prospective validation, integration with infection-preventionist workflows, and regulatory clarity for surveillance-oriented (as opposed to diagnostic or treatment-directing) AI tools [4]. At least one FDA-authorized sepsis-prediction tool has recently completed a formal development-and-validation pathway, illustrating that regulatory routes for this category of AI exist but have so far been used by relatively few surveillance and prediction tools [13].

7. Future Directions

Based on the patterns identified above, several priorities emerge for future research and implementation science in AI-driven infection surveillance:

1. Mandatory multi-site external validation before broad deployment, reported with calibration plots and clinically meaningful metrics (positive predictive value, alert lead time, workload reduction) rather than discrimination statistics alone.
2. Greater use of hybrid structured-data-plus-NLP architectures, given the consistent sensitivity gains observed when unstructured clinical text is incorporated.
3. Human in the loop implementation models that use AI for case prioritization and workload reduction rather than autonomous HAI determination, preserving infection-preventionist oversight.
4. Standardized, transparent reporting of model development and validation (e.g., following TRIPOD-AI or equivalent guidance) to enable cross-study comparison and meta-analysis.
5. Prospective, outcome-oriented studies measuring downstream clinical impact (time to appropriate therapy, HAI rates, mortality, length of stay) rather than model discrimination in isolation.
6. Explicit evaluation of algorithmic bias and performance equity across patient subgroups, care settings, and documentation practices.
7. Clearer regulatory and health-system governance pathways for surveillance- and prediction-oriented AI tools, distinct from diagnostic or treatment-directing AI.

8. Conclusion

AI-driven approaches particularly those combining structured EHR data with NLP of clinical narratives have demonstrated real potential to improve the sensitivity, timeliness, and efficiency of healthcare-associated infection surveillance relative to conventional manual chart review [16], [17]. At the same time, the well-documented external-validation failures of widely deployed sepsis early-warning tools show that strong internal performance does not guarantee real-world benefit, and that poorly calibrated systems can actively harm clinical workflows through alert fatigue [11], [12]. The most defensible path forward treats AI as an augmentation of, rather than a replacement for, infection prevention expertise: rigorously externally validated, transparently reported, embedded in human-in-the-loop workflows, and evaluated on clinically meaningful outcomes rather than model accuracy alone. With these safeguards, AI-driven infection surveillance is well positioned to become a standard component of hospital infection prevention and control programs over the coming decade.

References

1. Alghamdi, S., et al. (2025). *Harnessing artificial intelligence for infection control and prevention in hospitals*. *Saudi Medical Journal, 46*(4), 329–340.

2. Suvvari TK, Kandi V. Artificial intelligence enhanced infectious disease surveillance - A call for global collaboration. New Microbes New Infect. 2024 Oct 3;62:101494. doi: 10.1016/j.nmni.2024.101494. PMID: 39429727; PMCID: PMC11490829.https://pmc.ncbi.nlm.nih.gov/articles/PMC11490829/
3. Villanueva-Miranda I, Xiao G and Xie Y (2025) Artificial intelligence in early warning systems for infectious disease surveillance: a systematic review. Front. Public Health 13:1609615. doi: 10.3389/fpubh.2025.1609615
4. Li JH, Tseng YJ, Chen SH, Chen KF. Artificial intelligence in infection surveillance: Data integration, applications and future directions. Biomed J. 2026 Apr;49(2):100929. doi: 10.1016/j.bj.2025.100929. Epub 2025 Nov 6. PMID: 41205676; PMCID: PMC13091077.
5. Villanueva-Miranda I, Xiao G and Xie Y (2025) Artificial intelligence in early warning systems for infectious disease surveillance: a systematic review. Front. Public Health 13:1609615. doi: 10.3389/fpubh.2025.1609615
6. Li JH, Tseng YJ, Chen SH, Chen KF. Artificial intelligence in infection surveillance: Data integration, applications and future directions. Biomed J. 2026 Apr;49(2):100929. doi: 10.1016/j.bj.2025.100929. Epub 2025 Nov 6. PMID: 41205676; PMCID: PMC13091077.
7. Centers for Disease Control and Prevention. (2025). *Healthcare-associated infections (HAIs): Reports and data*. https://www.cdc.gov/healthcare-associated-infections/
8. Chea, N., Li, R., Eure, T., et al. (2026). Health care–associated infections in U.S. hospitals, 2023 versus 2015. *New England Journal of Medicine, 395*, 255–266. https://doi.org/10.1056/NEJMoa2510881
9. Alvaro Flores-Balado, Carlos Castresana Méndez, Antonio Herrero González, Raúl Mesón Gutierrez, Javier Arcos, María Dolores Martín-Ríos the Surgical Site Infection Surveillance Group. and retrospective cohort validation of an algorithm for surgical site infection surveillance after hip replacement surgery using natural language processing and extreme gradient boosting. (2023). *MedRxiv*, **doi:** https://doi.org/10.1101/2023.01.17.23284669Design
10. El Arab, R. A., Almoosa, Z., Alkhunaizi, M., Abuadas, F. H., & Somerville, M. (2025). Artificial intelligence in hospital infection prevention: An integrative review. *Frontiers in Public Health, 13*, 1547450. https://doi.org/10.3389/fpubh.2025.1547450
11. Valan B, Prakash A, Ratliff W, et al. Evaluating the Portability of SepsisWatch: A Multi-Site External Validation of a Sepsis Machine Learning Model. medRxiv; 2024. DOI: 10.1101/2024.03.22.24304753.
12. Bhargava, A., López-Espina, C., Schmalz, L., Khan, S., Watson, G., Urdiales, D., Updike, L., Kurtzman, N., Dagan, A., Doodlesack, A., Stenson, B., Sarma, D., Reseland, E., Lee, J., Kravitz, M., Antkowiak, P., Shvilkina, T., Espinosa, A., Halalau, A., … Shapiro, N. (2024). FDA-Authorized

AI/ML Tool for Sepsis Prediction: Development and Validation*nejm ai*, *1*(12). https://doi.org/10.1056/AIoa2400867

13. Baddal B, Taner F, Uzun Ozsahin D. Harnessing of Artificial Intelligence for the Diagnosis and Prevention of Hospital-Acquired Infections: A Systematic Review. Diagnostics (Basel). 2024 Feb 23;14(5):484. doi: 10.3390/diagnostics14050484. PMID: 38472956; PMCID: PMC10930720.
14. Alhusain FA. Harnessing artificial intelligence for infection control and prevention in hospitals: A comprehensive review of current applications, challenges, and future directions. Saudi Med J. 2025 Apr;46(4):329-334. doi: 10.15537/smj.2025.46.4.20240878. PMID: 40254319; PMCID: PMC12010500.
15. Antonelli A, Ales ME, Chiecca G, Dalla Valle Z, De Ponti E, Cereda D, Crottogini L, Renzi C, Signorelli C, Moro M. Healthcare-associated infections and antimicrobial use in acute care hospitals: a point prevalence survey in Lombardy, Italy, in 2022. BMC Infect Dis. 2024 Jun 25;24(1):632. doi: 10.1186/s12879-024-09487-7. PMID: 38918691; PMCID: PMC11197227.
16. Shi, J., Liu, S., Pruitt, L. C. C., Luppens, C. L., Ferraro, J. P., Gundlapalli, A. V., Chapman, W. W., & Bucher, B. T. (2020). Using natural language processing to improve EHR structured data-based surgical site infection surveillance. *AMIA Annual Symposium Proceedings*, *2020*, 794–803.
17. Agostinho, A., Chalot, E., Teixeira, D. *et al.* Semi-automated surveillance of surgical site infections using machine learning and rule-based classification models. *npj Digit. Med.* **8**, 617 (2025). https://doi.org/10.1038/s41746-025-01989-1
18. van der Werff SD, van Rooden SM, Henriksson A, Behnke M, Aghdassi SJS, van Mourik MSM, Nauclér P. The future of healthcare-associated infection surveillance: Automated surveillance and using the potential of artificial intelligence. J Intern Med. 2025 Aug;298(2):54-77. doi: 10.1111/joim.20100. Epub 2025 Jun 5. PMID: 40469046; PMCID: PMC12239059.
19. Wong, A., Otles, E., Donnelly, J. P., et al. (2021). External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients. *JAMA Internal Medicine, 181*(8), 1065–1070. https://doi.org/10.1001/jamainternmed.2021.2626