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EDITORIAL COMMENTARY

Artificial Intelligence and the Future of Healthcare-Associated Infection Surveillance: Bridging Precision, Partnership, Practice, and People

Mamdooh Alzyood

Department of Psychology, Health and Professional Development, Oxford Brookes University, Oxford, United Kingdom

(See the Viewpoints by Morgan et al on pages 473–9.)

Artificial intelligence (AI) holds significant potential to transform how health systems identify, monitor, and prevent healthcare-associated infections (HAIs), offering both promise and complexity as hospitals worldwide continue to grapple with these persistent challenges. From electronic health record (EHR) mining to natural language processing and predictive analytics, AI is beginning to move from concept toward clinical reality. Yet its integration into infection surveillance remains limited, with most applications still confined to pilot studies or retrospective analyses. In this issue of *Clinical Infectious Diseases*, Morgan et al address this emerging frontier through a timely viewpoint on the use of generative AI for infection surveillance, describing how large language models may enhance case detection and reporting accuracy [1]. Their work reflects a growing consensus that AI should complement, rather than replace, infection prevention specialists, strengthening interpretation, improving efficiency, and reshaping how hospitals anticipate infection risks.

Morgan et al [1] make 3 important contributions to this evolving discussion. First, they clarify how generative AI differs from earlier machine learning approaches, particularly in its capacity to interpret unstructured clinical narratives. Second, they outline a realistic implementation pathway that aligns with existing infection surveillance frameworks. Third, they appropriately temper optimism with calls for prospective validation and robust human oversight. Their viewpoint situates generative AI within established surveillance systems, demonstrating how language models can align infection definitions with national and international reporting standards. This is a valuable contribution at a time when enthusiasm for AI can easily outpace careful evaluation. The article encourages reflection not only on what AI can achieve but also on how its development, governance, and validation processes must evolve to ensure responsible adoption in infection prevention practice. While Morgan et al provide a thoughtful synthesis, the viewpoint would have benefited from a deeper discussion of potential failure modes, including when and why generative AI might misclassify infections, and clearer guidance on the oversight mechanisms required when algorithmic and clinical judgments diverge. Their analysis focuses mainly on technical feasibility, giving less attention to implementation barriers such as interoperability with legacy systems and resistance among infection prevention teams who may perceive AI as a threat to professional autonomy.

Recent evidence from large-scale analyses reinforces the growing potential of AI in infection surveillance. Machine-learning tools have reduced surveillance workload by up to 85%, lowered HAI incidence from 1.31% to 0.58%, and achieved area under the curve (AUC) values approaching 0.90 for surgical site and urinary tract infection detection [2]. A study applying a random forest algorithm to data from more than 6000 hospitalized patients demonstrated a 71% reduction in record review time and a 42% increase in true infection detection without loss of specificity [3]. Meta-analyses and systematic reviews report similar diagnostic accuracy, noting that explainable AI approaches such as SHapley Additive exPlanations (SHAP) improve clinician confidence and model transparency [4, 5]. Broader syntheses further confirm that AI-supported early warning systems can detect outbreaks earlier and integrate multiple data streams more efficiently than traditional methods [6]. Collectively, these findings suggest that while the evidence base for AI in infection surveillance is strengthening, its consistent translation into measurable clinical benefit remains a work in progress.

Real-world implementations are now generating important lessons on feasibility and adaptation. In the United States,

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Correspondence: M. Alzyood, Department of Psychology, Health and Professional Development, Oxford Brookes University, Headington Campus, Oxford, Oxfordshire, OX3 0BP, UK (malzyood@brookes.ac.uk).

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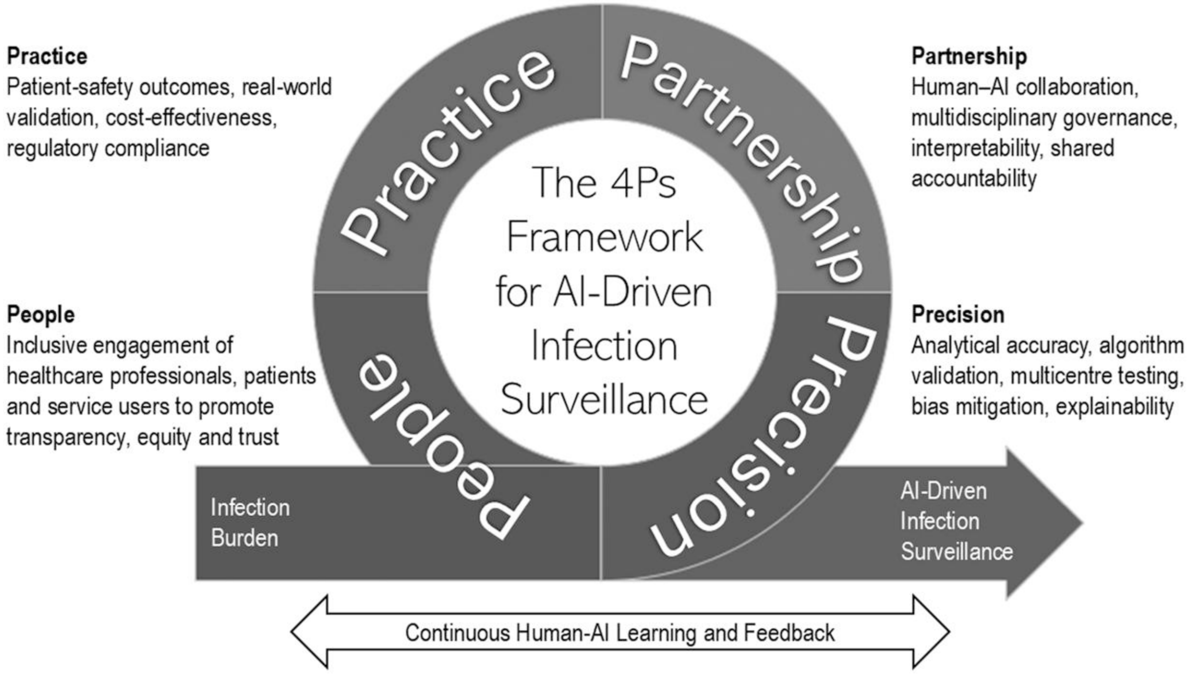

Figure 1. The 4Ps framework for AI-driven infection surveillance, illustrating how precision, partnership, practice, and people combine to strengthen patient safety and infection prevention. The loop labeled Continuous Human-AI Learning and Feedback.

models such as GPT-4 and Mixtral performed accurately against National Healthcare Safety Network (NHSN) definitions for central line and catheter-associated infections when prompts were structured correctly [7]. In Brazil, automation expanded from pilot testing to hospital-wide deployment, producing measurable improvements in reliability and workload [3]. Programs in Italy, Denmark, and Canada reported substantial reductions in manual effort and earlier identification of infection clusters [2]. Collectively, these examples indicate that AI-driven surveillance is advancing beyond experimental proof of concept, although readiness, regulation, and validation capacity still vary considerably across health systems.

Despite this progress, several limitations persist. Most systems still rely on retrospective or semiautomated designs rather than fully real-time learning architectures. Validation across diverse settings remains limited, as many algorithms are trained on single-center data that may not capture the complexity of multicentre workflows or regional epidemiology. Three biases are particularly concerning: documentation bias, where AI performance depends on the completeness and style of clinical notes; selection bias, where training data may over-represent certain patient populations or infection types; and confirmation bias, where models trained on historical classifications risk perpetuating outdated or inconsistent practices. Notably absent from most studies, including [1], is discussion of how these biases interact in practice, where documentation quality varies markedly between day and night shifts, between teaching and community hospitals, and across different specialties. Model transparency, reproducibility, and version control continue to hinder trust. External validation, defined as prospective testing of algorithms across institutions with different EHR systems, patient demographics, and infection prevention protocols, remains uncommon [2, 3, 5]. Without such validation, an algorithm that performs well in 1 academic medical center may fail entirely in another setting. Addressing these challenges requires sustained investment in shared data resources, explainable models, and open benchmarking frameworks that allow performance to be assessed transparently.

Yet technical progress alone is insufficient; ethical and governance standards must evolve in parallel to ensure responsible and trustworthy adoption. Data privacy, equitable access to AI infrastructure, and algorithmic bias are not peripheral considerations but central determinants of implementation success. Collaborative data ecosystems and shared learning models are essential to reduce regional disparities and maintain consistent standards in epidemic intelligence [8]. The Organisation for Economic Co-operation and Development (OECD) highlights transparency, human oversight, and continuous data quality assurance as prerequisites for the responsible use of AI in digital surveillance and clinical practice [9]. These principles must now evolve into enforceable governance structures to ensure that AI strengthens, rather than fragments, infection surveillance through proprietary silos and unverified claims.

Table 1. The 4Ps Framework for Artificial Intelligence in Healthcare-Associated Infection (HAI) Surveillance

Pillar	Definition and Focus	Key Considerations	Example Elements
Precision	Focuses on algorithm development, analytical accuracy, and technical validation of AI models for HAI detection	Algorithms must be rigorously validated across diverse settings and populations. Documentation bias, selection bias, and confirmation bias must be identified and mitigated. External, multicenter validation against standardized benchmarks is essential before deployment	• Multicenter validation • Bias assessment • Performance metrics (sensitivity, specificity, AUC) • Explainable AI methods • Reproducibility protocols
Partnership	Defines collaboration among AI systems, healthcare organizations, technology developers, and regulators	AI must integrate seamlessly with existing infection surveillance infrastructure. Interoperability with electronic health record systems, data-sharing agreements, and vendor accountability are critical. Clear governance structures prevent proprietary silos	• AI-EHR integration • Data-sharing protocols • Vendor accountability • Regulatory frameworks • Cross-institutional collaboration
Practice	Addresses real-world implementation, measuring patient safety outcomes and surveillance effectiveness in clinical settings	Implementation should demonstrate measurable improvements in patient outcomes, using standardized metrics such as those defined by CDC or NHSN. Cost-effectiveness, equitable access across different resource settings, and regulatory compliance ensure sustainable adoption	• Patient safety outcomes • Infection-related mortality • Cost-effectiveness analysis • Equitable access • Regulatory compliance • Real-world validation studies
People	Centers on human stakeholders, including infection prevention professionals, clinicians, patients, and the wider healthcare workforce	Workforce training ensures infection prevention specialists can interpret, audit, and, when necessary, override AI outputs. Clinical oversight maintains accountability, while patient and public engagement builds trust. Addressing professional concerns about autonomy and job security is essential	• Workforce training programs • Clinical oversight mechanisms • Patient engagement • Professional development • Change management strategies

The 4Ps framework provides a foundational structure for integrating AI into HAI surveillance. Each pillar represents a critical domain necessary for effective, ethical, and sustainable implementation. The framework is intentionally adaptable across healthcare systems and resource settings.

Abbreviations: AUC, area under the curve; CDC, Centers for Disease Control and Prevention; EHR, electronic health record; NHSN, National Healthcare Safety Network.

In parallel with governance reform, progress will rely on refining algorithms and fostering enduring partnerships among infection prevention professionals, clinicians, and data scientists. Effective collaboration requires interpretability, auditability, and demonstrable improvements in patient safety outcomes. Future research should prioritize prospective multicenter validation, integration with antimicrobial stewardship initiatives, and outcome measures such as infection-related mortality and cost avoidance. Across all settings, the ultimate goal is to ensure that AI enhances human expertise, supports professional judgment, and reduces administrative burden. These priorities highlight the need for a coherent framework that links analytical precision, multidisciplinary partnership, practical implementation, and meaningful engagement of healthcare professionals, patients, and service users. Such inclusivity will provide a strong foundation for sustainable AI integration in infection surveillance.

As infection surveillance enters a phase of applied AI, the challenge now lies in consolidating precision, partnership, practice, and people into a coherent framework. This commentary proposes the 4Ps approach as a practical pathway for advancing AI-driven infection prevention while maintaining clinical integrity and ethical governance. Drawing on emerging evidence and international experience, a structured model can be articulated through the 4Ps framework: precision, partnership, practice, and people (Figure 1). Further operational details for each pillar are presented in Table 1.

Precision ensures analytical accuracy and methodological clarity; partnership reinforces collaboration between human insight and technological innovation; practice grounds implementation in patient safety and effective infection surveillance; and people centers the process on transparency, equity, and trust among both the public and the healthcare workforce. Although some may view the addition of people as broadening the framework, its inclusion recognizes that human engagement, clinical oversight, and patient confidence are integral to sustainable AI adoption. The people pillar anchors the framework in ethical practice and inclusivity, ensuring that technological progress remains aligned with the social and professional realities of infection prevention.

The global evidence now points to 1 clear conclusion: Precision without partnership will not transform practice, and automation without accountability will not advance patient safety. Three actions are essential. First, infection prevention organizations should establish multicenter validation registries to enable prospective algorithm testing across diverse healthcare settings. Second, regulatory bodies need to define standardized benchmarks for AI performance in HAI detection, aligned with existing diagnostic evaluation frameworks. Third, healthcare systems must invest in equipping infection prevention specialists to interpret, audit, and, when necessary, override AI outputs, ensuring that technology enhances rather than replaces clinical judgment. As healthcare enters the era of intelligent surveillance, success will depend on our collective capacity to connect precision with purpose, partnership with people, and data with the human values that define infection prevention.

Notes

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