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Beyond prediction: Translating artificial intelligence into infectious-disease action

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Infectious diseases are rarely understood from a single source. Clinical findings, laboratory results, imaging, pathogen genomes, antimicrobial susceptibility, environmental conditions and population surveillance each describe only part of the problem. Artificial intelligence (AI) can connect these signals, but a risk score has little value unless it reaches the right person, at the right time, and leads to an action that can be implemented. Recent work has established important opportunities in diagnosis, outbreak detection, antimicrobial resistance and drug discovery, while also showing that evidence of routine clinical and public-health benefit remains limited (Miglietta et al., 2026; Odone et al., 2026; Wong et al., 2023).

Retrospective model development usually starts with a convenient dataset and a confirmed label. Real decisions begin with incomplete information, delayed confirmation, changing prevalence and unequal consequences of error. A model trained on confirmed cases may fail among untested patients, in laboratories using different assays, or during circulation of a new lineage. Conventional measures such as sensitivity, specificity and area under the curve do not show whether an alert arrived early enough, changed treatment, reduced transmission or created an avoidable burden. Reproducibility and external validity remain persistent concerns, particularly when models move between institutions and populations (McDermott et al., 2021).

From prediction to action

The proposed Infectious-Disease Intelligence-to-Action (IDIA) pathway therefore treats prediction as one stage of a wider decision system. As shown in Figure 1, relevant evidence is first selected for the intended clinical or public-health decision. The data are then aligned by time, location, format, quality and local epidemiology. The third layer estimates infection, severity, transmission or resistance together with uncertainty. The fourth layer tests calibration, subgroup safety, drift, security and human authority. The final layer converts the evidence into a feasible action, followed by outcome feedback. Governance, data sovereignty and resource constraints apply across all five layers.

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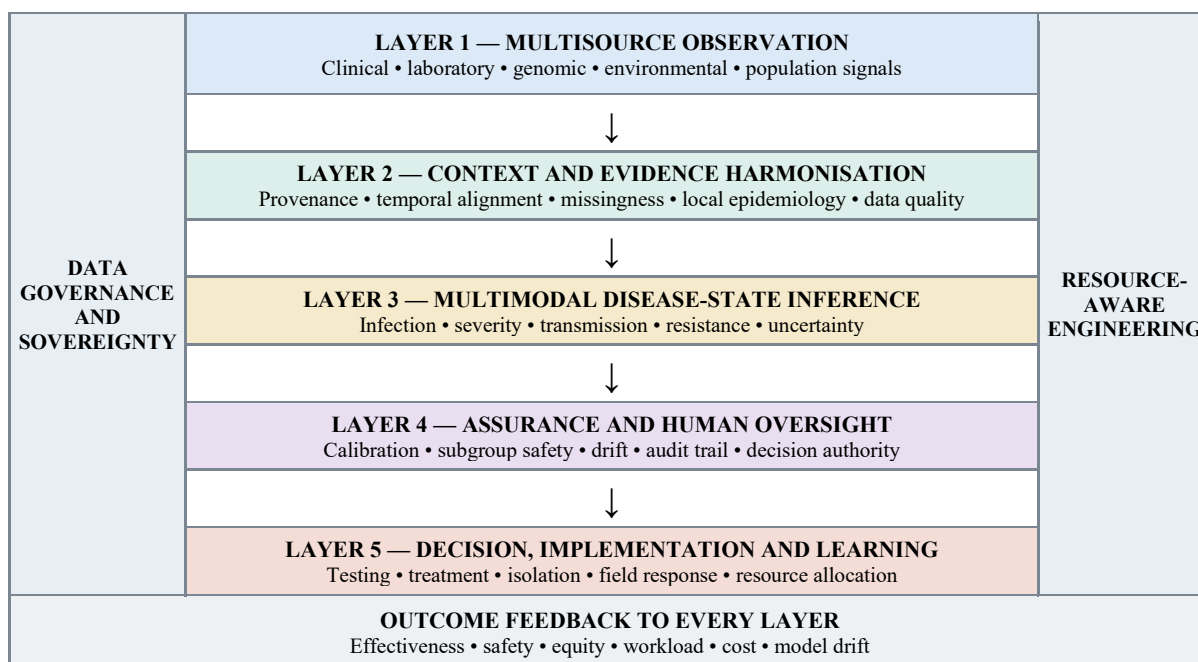


Figure 1. Infectious-Disease Intelligence-to-Action pathway for linking evidence to accountable clinical and public-health decisions

The decision can be expressed compactly as follows:

$$a_t^* = \arg \min_{a \in A_t} [L_H(a) + \lambda_C C(a) + \lambda_E E(a) + \lambda_U U(a)], \quad g_k(a, D_1; t) \leq 0$$

The selected action should minimize expected health loss while accounting for operational cost, equity and uncertainty. The feasible action set may include further testing, treatment initiation or de-escalation, isolation, cluster investigation, vector control, stock allocation or risk communication. The weights and constraints cannot be fixed by the model developer alone; they require clinical, public-health and community judgement.

Priority disease pathways

The same pathway supports different infectious-disease problems without forcing them into one general model. For tuberculosis and respiratory infections, useful endpoints include time to confirmatory testing, time to treatment, false reassurance and successful linkage to care. For antimicrobial resistance and sepsis, the relevant outcomes include time to effective therapy, unnecessary broad-spectrum exposure, adverse events and de-escalation. The global burden of bacterial antimicrobial resistance is already substantial and is projected to rise, making decision-focused systems more urgent (GBD 2021 Antimicrobial Resistance Collaborators, 2024). Recent reviews describe valuable applications in resistance prediction, stewardship and antibiotic discovery, but clinical benefit still depends on timeliness and local treatment options (Cesaro et al., 2025; Howard et al., 2026). For climate-sensitive and zoonotic threats, human cases should be interpreted alongside animal, vector, climate and event-based surveillance, consistent with the World Health Organization's collaborative-surveillance approach (World Health Organization, 2023).

Requirements for credible implementation

Resource restrictions have to be built into the design from the beginning. Rather than decreasing inequity, systems that require constant access to the cloud, complete electronic records, or rapid sequencing may actually increase it. They should be able to continue safely in the absence of a data source, log reasons for unavailability of information and be validated across facilities, seasons, patient groups, devices and laboratory workflows. While federated learning might facilitate multi-institutional development without centralising all records, it does not address questions of ownership, maintenance, cybersecurity or benefit sharing (Rieke et al., 2020). Such questions are particularly relevant in contexts where the sustainability of systems is threatened by the use of disparate systems and dependence on external platforms (Tiffin et al., 2019).

Evaluation should contain retrospective validation, silent prospective testing, implementation studies and post-deployment surveillance. The main endpoint must match the promised benefit: earlier appropriate testing or treatment, fewer preventable cases, safer antimicrobial use, acceptable workload, equitable performance and affordable operation. Local institutions should retain evidence of performance, histories, audit records and procedures for suspension. Human oversight needs to add clear authority, not merely a symbolic clinician in the workflow.

The next stage of AI for infectious disease should therefore be judged by the quality of the intelligence-to-action pathway, not just model scale or benchmark accuracy. Prior to the development of the model, the multidisciplinary teams must define the decision, the feasible response, the acceptable uncertainty and the outcome. These systems will demonstrate progress in enhancing timely care, responsible use of antimicrobials, outbreak response and equity, under the conditions in which health services actually operate.

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