# Global advances in health artificial intelligence: a workforce imperative

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**The global health workforce is approaching a breaking point, driven by administrative overload, inefficient workflows, burnout, and accelerating retirements, with a projected global shortfall of 11 million health professionals by 2030. This urgency coincides with the rapid emergence of clinical artificial intelligence (AI) tools, especially generative systems now embedded in documentation, triage, and workflow support. Therefore, AI should be framed less as a substitute for clinicians than as a retention strategy that preserves careers, expertise, and the human core of care. High-impact uses include ambient documentation, coding support, scheduling and demand prediction, claims and billing support, and inbox triage—tools that can reduce clerical burden and return time to caring, teaching, and leadership. Workforce shortages also create an ethical and geopolitical dilemma; reliance on international recruitment can deepen global inequities, whereas responsible AI deployment might ease competition for scarce talent and expand capacity in lower-resource settings. Yet, AI will not fix dysfunctional systems by default; poorly designed implementation can shift burdens, erode confidence, and widen gaps in health-care quality, access, and clinician wellbeing. Practice must remain clinician-led, patient-centred, and grounded in shared decision making. The policy priority is expertise amplification, not workforce replacement.**

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## Introduction

The global health workforce is buckling under sustained strain. Escalating health expenditures have fuelled a disproportionate investment in administration among health delivery services (eg, health management and physician offices) and payors, inefficient management, and standardised, throughput-driven workflows that compress clinician–patient interactions, eroding morale and accelerating burnout, early disability, and premature retirement. Demographic shifts, including population ageing in high-income countries and a parallel ageing of the current clinical workforce, are compounding the crisis. By 2030, the world faces an estimated shortfall of 11 million health-care professionals, which will be felt disproportionately in regions with the highest disease burden.[1] In this environment, artificial intelligence (AI) is often framed as a panacea because it appears to address workforce scarcity, administrative burden, rising demand, and cost pressure at the same time. This framing is understandable but incomplete; implementation quality, governance, and workflow redesign determine whether AI improves care safely at scale. The most impactful use of AI might therefore be to retain clinicians, preserve expertise, and support transfer of knowledge to future generations.

## Retention, not replacement

We need to retire the false dichotomy of person versus machine. The question is no longer whether AI will replace clinicians, but how it will reshape health-care work and sustain the workforce we need. Anything else will only contribute to an already vicious cycle of job-loss anxiety and underappreciation among clinicians. Even systems with centralised control are recognising the limits and risks of AI-driven substitution. In China, where initial health AI policy focused on building so-called AI doctors, the National Health Commission issued a 2022 directive explicitly prohibiting autonomous diagnoses.[2] Instead, AI must support human, empathetic shared decision making between health-care professionals, patients, and their families. Meanwhile, Singapore, Canada, the USA, and more recently, Europe are increasingly aligned in their ethical and regulatory approaches to health AI,[3] and are deploying AI to do what health-care professionals should not have to do. The following sections outline several examples of tools leveraging AI's unique capabilities to support the workforce.

### Ambient note transcription

Ambient AI scribes are being rapidly adopted; early-adopter health systems report improved clinician experience and reductions in self-reported burnout relative to pre-deployment baseline. In a 6-week pilot survey, Mass General Brigham (Boston, MA, USA) reported a 40% relative reduction in self-reported burnout (n=223) and less time outside work completing notes (from ≥90 min to <30 min; n=124).[4]

Although ambient documentation and generative tools can reduce clerical workload, concerns remain regarding factual inaccuracy, omission, bias, and automation complacency in patient-facing advice and note generation. The evidence base is growing but heterogeneous across settings; therefore, deployment should include human sign-off for patient-facing outputs, structured discrepancy logging, incident escalation pathways, and periodic sampling audits.

### Coding and billing

Translating clinical notes into billing codes is a time-consuming, error-prone task.[5] AI systems now outperform manual entry in speed and consistency. In one study, natural language processing applied to more than 120 000 free-text chief complaints from a statewide health information exchange extracted clinical concepts and assigned 88% of them to the correct ICD-10-Clinical Modification category. However, only 42% of concepts were assigned the exact code, illustrating both the promise and the current limits of automated coding in front-line care.[6] Another system analysed entire clinical notes to assign disease-specific ICD codes, achieving an area under the receiver operating characteristic curve of 0·91–0·92 across two electronic health record systems.[7] Such tools could ease documentation burdens and reduce clerical strain on clinicians.

### Insurance claim filing and adjudication

Risk adjustment models are employed to prevent adverse selection (the disproportionate enrolment of individuals at high-risk of insurance claims into a single plan), anticipate budgetary reserve needs, and offer care management services to individuals at high risk of costly outcomes (eg, hospitalisation, complications, and prolonged stays in care). An AI model trained on 1 million US patients reduced misestimation of cost by US$3·5 million per 10 000 insured people in one study compared with linear regression.[8]

### Hospital occupancy and staffing prediction

AI helps match staff to real-world demand. Models that consider prescription and procedure data identify what clinicians actually do in practice, as their specialty designation can be ambiguous, giving planners a clearer picture of workforce supply. For example, a family physician may focus on women's health rather than broad spectrum general medicine.[9] At the same time, AI models support reliable next-day bed and staffing calls.[10] The outcome is fewer last-minute changes, less overtime, and a workforce that feels planned for, rather than perpetually reactive.

### Smart scheduling

Forecasting visit length and patients not attending appointments (no-shows) is central to running clinics that neither over-run nor sit idle. A machine learning scheduler piloted in a cardiology practice cut consultation-time prediction error by roughly half and, in the process, uncovered practical insight such as first-visit status and planned imaging.[11] In primary care community-health centres, a complementary model analysing more than 70 000 appointments showed that just a handful of variables—including time between booking and visit, previous no-shows, and not owning a mobile phone—explain most no-shows.[12] By spacing visits realistically and backfilling likely gaps, such tools spare clinicians the chronic over-runs and idle stretches that reduce morale and drive turnover.

### Smart cost risk prediction

Health systems aim to identify patients at risk for costly outcomes (prolonged stays, readmissions, etc) and intervene early. One study found that deep learning-derived predictions of patient outcomes far outperformed traditional risk scores.[13] AI models can even predict diagnosis-related group codes (and associated costs) early during hospital stays with high accuracy.[14]

Effectively deploying these tools means more time for clinicians to care, teach, and lead. What is happening without these tools is more sobering—clinicians burning out so severely they abandon the profession altogether. In 2024, hospitals in the USA reported nurse turnover of 16%, and 42% of hospitals operated with nurse vacancy rates above 10%, citing unsustainable workloads.[15] In the 2022 national nursing workforce survey, a majority of nurses said they would not recommend the profession to younger generations.[16] If this trend continues, we face a future in which no number of medical or nursing school slots will compensate for what we have lost: not just labour, but vocation.

## AI as a geopolitical and ethical workforce strategy

We face an ethical emergency—if health-care systems in high-income countries rely on importing foreign clinicians to fill staffing gaps, they deepen global inequality. WHO has already named 55 countries vulnerable to outbound health worker migration.[17] These nations, which often have fragile health systems, cannot afford to lose talent.

Here, AI is more than a technical tool; it becomes a geopolitical strategy. A US hospital using AI to double radiology throughput might be able to avoid hiring an overseas radiologist. A National Health Service chatbot resolving patient queries at scale in the UK can potentially spare the need to recruit a nurse from Ghana. In this framing, AI is not just about efficiency. It is about avoiding futile competition for scarce human capital.

Of course, this path demands responsibility. Wealthier nations must also invest in scaling AI capacity in lower-income settings. Autonomous AI for front-line screening, as shown in a Bangladesh study on diabetic retinopathy that boosted clinical productivity by 40%, offers a glimpse of how targeted deployment could extend diagnostic access without overwhelming specialist pipelines.[18] Rwanda's national AI chatbot, Babyl, reached millions with triage and scheduling services between 2019 and its 2023 wind-down, demonstrating both the operational feasibility and the financial-sustainability challenges of nationwide AI-first care.[19] WHO has expanded its 2021 endorsement of computer-aided detection for tuberculosis screening, evaluating additional software products in its 2025 policy update.[20] These are early signs that AI can serve as a global public good.

In general, AI equity will not happen by accident. If model-development capacity, compute access, and high-quality training data remain concentrated in a small number of high-income settings, efficiency gains might widen rather than reduce international workforce

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disparities. Ethical strategy therefore requires actionable mechanisms: shared evaluation standards, reciprocal validation networks, financing pathways for local capacity-building, and interoperability baselines that support partnership with lower-resource systems.

## Not just technology hubs: which regions are ready?

Country strategy should be framed as a practical choice among three pathways: build domestic systems, adapt external systems with local controls, or federate through shared standards and reciprocal validation. Canada and Singapore illustrate how policy continuity and national digital infrastructure can accelerate implementation.[3] China's rapid deployment has also been enabled by substantial policy support and reimbursement-linked pathways, while governance constraints on autonomous diagnosis remain explicit.[2] Australia illustrates why context matters: ICD-10-Australian Modification coding architecture can materially affect model transferability, billing integration, and documentation reliability, making adaptation layers or selective domestic development preferable in some settings.[21] The European Health Data Space and related cross-border initiatives indicate a parallel pathway based on interoperability and coordinated governance.[22]

The US paradox in health AI is one of innovation without coherence. US firms lead in core digital-health products, yet fragmentation in interoperability and governance continues to constrain national-scale implementation. At the same time, US systems are early adopters of generative tools for ambient documentation, inbox triage, and previsit workflow support.[23] These use cases are promising but require stronger safety governance and postdeployment monitoring as they scale.

The future of health AI is unlikely to be dominated by any single country or region. Leadership will be distributed, with different systems contributing strengths shaped by local institutions—for example, research and entrepreneurial capacity in the USA and other innovation hubs; governance leadership in Europe; rapid deployment and scaling in parts of Asia; and pragmatic implementation lessons from Rwanda and Australia for workforce-limited or geographically dispersed settings. Much more could be accomplished even faster and more cost-effectively if the major current players on all continents would synergistically join forces.[22] Given the current geopolitical climate, this seems unlikely, although international collaboration has been well proven in other high-tech areas such as space exploration in the not too distant past.[24]

Low-income and middle-income countries are increasingly contributing implementation evidence rather than only future promise. Current examples include AI-supported tuberculosis screening in imaging workflows, triage and self-management support applications, and targeted prediction models for constrained care settings.[18,20] These use cases indicate that readiness depends on local validation, workflow adaptation, workforce training, and continuity of governance.

But readiness is not destiny. AI layered on top of dysfunction will not repair broken health-care systems. A digitised burden remains a burden, often shifting work rather than reducing it. Clinicians already tethered to an excessive number of electronic messages throughout the day might find new tools adding to their workload, not capacity. When deployed as afterthoughts, such systems risk compounding frustration rather than relieving it.

## What work will look like in 2030: new skills, not just more technology

The World Economic Forum's *Future of Jobs Report 2025* anticipates a net gain in jobs by 2030—but with transformed skill sets.[25] In health care, we are already seeing the rise of hybrid roles: AI health navigator, digital scribe supervisor, and telehealth integrator. The best future clinicians will not be those who fear AI, but those who know when to trust it and when to over-ride it.

Nursing must be central to workforce-focused AI strategy, from design and governance through to implementation. As the largest professional segment of the health workforce, nurses are crucial to safe implementation, continuity of care, and patient trust.[26] AI might reduce selected documentation and coordination burdens, but nursing is not reducible to automatable tasks; relational and therapeutic care remains fundamental. Nursing education should integrate AI literacy and critical appraisal, and institutions should assign nurses formal safety–governance roles across development, deployment, and ongoing monitoring.[27]

For more on the **European Health Data Space** see https://www.european-health-data-space.com/

Moreover, AI could help some experienced clinicians remain in practice longer by reducing administrative burden and workflow friction. This pattern is plausible and increasingly observed,[28] but stronger longitudinal evidence is still needed to quantify retention effects across settings. With retirement waves looming in Europe and North America, even modest retention gains could materially improve system resilience.

What is less discussed in the literature as well as by governments and industry is how AI might fracture professional identities. When algorithms outperform humans in narrow tasks, some clinicians experience deskilling or loss of clinical confidence.[29] Clinical education institutions should respond with explicit competency pathways: model-limit literacy, calibration exercises against independent clinical reasoning, simulation-based error recognition, and assessment formats that reward justified disagreement with algorithmic outputs when clinically appropriate.[30]

We might also see deeper stratification within the workforce. High-resource systems will train AI-augmented clinicians, whereas others might become dependent on AI tools without understanding how they work. That divide is not just technical—it is epistemic. And it risks creating tiers of trust and autonomy across borders.

## From automation to amplification

The narrative should shift from automation to amplification. Health AI should not be framed as a headcount-reduction strategy, but as a clinical-capacity and retention strategy.[31] Policy responsibilities should be tiered across three levels: national (interoperability and safety standards, procurement guardrails, and equity-oriented financing); institutional (workflow redesign, model-monitoring governance, and accountability for drift and bias); and individual (verification norms, competency development, and protected time for oversight and patient communication). Within this framework, AI should support, not determine, care decisions; practice must remain clinician-led, patient-centred, and grounded in shared decision making, with explicit nursing and medical oversight and named organisational accountability. Minimum development standards should include predeployment external validation, local postdeployment monitoring, explicit accountability assignment, and procurement tied to proven safety performance rather than throughput alone.

We must confront potential backlash. When organisations deploy AI solely to force more output from an already depleted workforce, the effort will backfire. The paradox is that AI's greatest gift might be less about automated diagnosis or bespoke treatment than about preserving the humanity of medicine itself. Its long-term value will be realised only if design choices actively rehumanise practice, restoring clinicians' sense of purpose and professional efficacy rather than eroding them.[31] That commitment means safeguarding a care model in which clinicians can truly partner with patients, integrating clinical expertise with each patient's preferences and lived experience. AI systems that honour the principle to first, do no harm for both patients and practitioners have the greatest potential to reshape health systems around this core partnership.

## Conclusions and outlook

Health AI is no longer a futuristic promise; it is a strategic imperative. But the most powerful argument for health AI is not cost savings or diagnostic speed; it is workforce survival. The coming decade demands that we stop asking whether AI can replace clinicians and start asking how it can help us keep them. In that reframed question lies the path to global equity, sustainable systems, and care that endures. To do anything less is to accept a future where care is rationed not by policy but by the limits of human exhaustion.

### Contributors

DCB had the initial idea and conceptualised the Viewpoint. TD wrote the first draft. KMM, TD, and DCB contributed additional content and edited the manuscript. All authors approved the final version.

### Declaration of interests

TD is Vice President for Marketing, Communications and Outreach, Institute for Operations Research and the Management Sciences; declares a collaboration on multiple studies with Digital Diagnostics, the manufacturer of LumineticsCore (IDx-DR), without receiving financial payments; and is co-chair of the Johns Hopkins Workgroup on AI and Healthcare. TD and KMM are co-leads of the Bloomberg Distinguished Professorship Cluster on Global Advances in Medical Artificial Intelligence at Johns Hopkins University. DCB declares no competing interests.

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