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How should we train clinicians for artificial intelligence in healthcare?

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Artificial intelligence (AI) is widely anticipated to be revolutionary in the field of healthcare. Globally, this is reflected in the explosion of academic publishing around clinical AI and the expanding list of AI medical devices regulated for clinical use.[1,2] Within the UK, the sustained strategic emphasis on clinical AI in the UK continues to be recapitulated, with more than £100 million committed in the last year.[3,4] This builds on prior infrastructure investments in the UK and consolidated guidance for vendors and adopters through the NHS AI and Digital Regulations Service (AIDRS).[5] However, more than a decade since initial AI medical devices were certified for use and after hundreds of millions of pounds of direct investment from the UK government, clinical AI applications in the NHS remain relatively scarce. We believe that the need for a workforce with the capacity and expertise to integrate clinical AI into everyday practice is a key contributor to this scarcity. Varied levels of engagement from all clinicians will be required if the translational gap for clinical AI is to be resolved.

In 2019, the Topol review highlighted that the success of AI innovation in the NHS will depend upon the creation of a workforce that is appropriately trained.[6] This need to inject digital health competencies into the NHS workforce was well demonstrated by a review of curricula for 71 postgraduate medical specialties in the UK finding few digital health competencies listed.[7] Elsewhere, academics have even suggested that the creation of a new clinical specialty may be part of the solution.[8] The Topol review motivated a collaboration between Health Education England (HEE) and the NHS AI lab to begin to address this by establishing the AI learning needs for the NHS workforce. In doing so, five different professional archetypes relating to AI were proposed, with a three-tiered conceptualisation of learning needs.[9] This important work has begun to operationalise the abstract need for workforce training expressed in the Topol review and elsewhere. For good reason, it stops short of prescribing learning outcomes to specific existent professional groups. This respects the autonomy of educationalists in healthcare across the UK to tailor training to their varied scopes of practice and delivery contexts. It also minimises conflict with educationalists and their trainees, who are already under significant time pressure to achieve competencies across congested curricula.[7,10] However, a lack of clear and authoritative answers to the questions of what needs to be learnt by whom could be problematic. Without it, low levels of AI literacy among clinical educationalists, competing priorities for space on clinical curricula and ambiguity over which professional body is responsible for AI training could sustain the long-reported skills gap (Fig. 1, Table 1).

While the educational needs of the NHS workforce extend beyond clinicians, they will form the focus of this article. As a practical contribution to the operationalisation of AI learning needs into real-world medical education, this commentary shares a view on 1) the relative distinctions of AI as a health technology, 2) the roles that clinicians should take in accommodating those distinctions and 3) the skills and knowledge that enable those roles to be performed.

Relative distinctions of clinical AI and associated learning needs

Clinical AI does not possess unique characteristics. We have all experienced low explainability from illegible clinic notes, diagnostic errors from our own clinical reasoning, or dysfunctional digital infrastructure that halts clinical workflow. These familiarities warn against 'AI exceptionalism'.[11] However, the tendency for certain constellations of characteristics to coexist with clinical AI technologies present distinct considerations for their use[12]:

Opacity

Sometimes referred to as the 'black box' phenomenon, this inability to understand why an AI tool produces certain outputs is often a compromise to accept when exploiting the high-performing computational complexity of some forms of AI. Some of these challenges have been reduced through the technical field of explainable AI (XAI), but these techniques are not always relevant or meaningful in clinical contexts.[13] Rather than knowing why an error has been generated, clinicians may mitigate against this distinction through their selection of AI products with a compelling and transparent evidence base, the design of AI-enabled workflows for which knowing why AI errors have occurred is not so important and an ability to spot signs of error occurrence, even if the errors cannot be explained.

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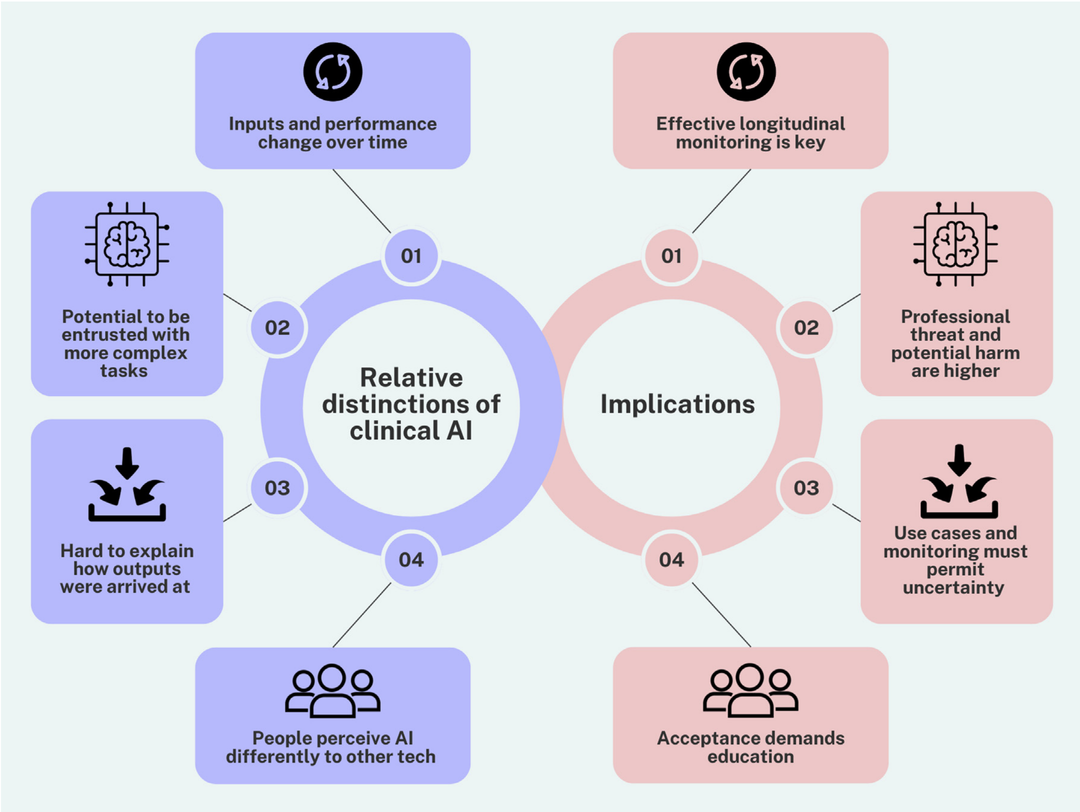

Fig. 1. The relative distinctions of clinical AI and their implications.

Table 1
Tailoring medical education to clinical AI and professional roles.

Educational target	Aim and scope of education	Delivery context	Risks to be mitigated
All clinicians **Foundational understanding of AI**	To make sense of clinical AI applications outside of their personal practice	Competencies achievable across a few hours in varied settings. To be delivered and mandated by a wide range of clinical educationalists	Distributed responsibility for the delivery and evaluation of training may lead to problematic variation across professions and geographies
Most clinicians **Product specific training**	To have an operational understanding of AI used in personal practice and to play a part in mitigating its risks	Clinical AI vendors should be responsible for initial training and ongoing educational support with input from adopter institutions	Dependency on AI vendors for training may fail to fully mitigate context-specific clinical risks
Some clinicians **Clinical champion competencies**	To develop and drive ideas for safe, effective and equitable AI use in their clinical domain understanding when additional expertise are required across the AI lifecycle	Bespoke training programmes delivered by multidisciplinary teams of clinical AI experts familiar with the NHS context	Scarcity of these individuals may incentivise their recruitment by AI vendors or redeployment to institutional or system-level roles within the NHS

Brittleness

The performance of clinical AI is sensitive to a wide variety of sociotechnical factors, which means that good performance cannot be presumed to continue at a single institution over time, nor between institutions as a product is scaled.[14] Without heavy investment by clinical AI vendors or system-level investment in monitoring infrastructure, this distinction will require resources and expertise for longitudinal monitoring of clinical AI at an institutional level. Because of the varied causes and manifestations of performance drift, this monitoring requires the coordination of a breadth of clinical, operational and technical expertise. This need is particularly important because of the relatively high-stakes decisions to which clinical AI is often targeted and the risk of synchronising harms across a whole system, which accompanies national scale deployment of individual medical devices.

Cultural novelty

While notions of ‘AI exceptionalism’ can be effectively contested in academic forums, the implementation of clinical AI is strongly influenced by a wide range of public and professional stakeholders.[15] This wider ecosystem of stakeholders are constantly exposed to positive and negative perspectives specifically targeted to AI, which carry varying accuracy and relevance to healthcare. This can lead to disincentives for clinicians to adopt AI through a perceived professional threat, institutional concerns over reputational risk or patients declining care through misunderstandings of AI operating principles. To manage the complexity associated with the broad range of existing perspectives on AI, clinicians must become comfortable discussing the topic with various stakeholders at both a general and product-specific level. This will promote transparency and trust among stakeholders and support each stakeholder in influencing the system from an informed position.

Clinician roles in AI-enabled care

Within the next few years it is likely that all clinicians will be exposed to patients who have received care through an AI-enabled care pathway. As a result, **all clinicians** would benefit from a foundational understanding of clinical AI, to support their interpretation of clinical records or referral patterns.[9] All clinicians can also expect to receive questions related to AI from patients, and the ability to comfortably construct basic responses will be advantageous. Much of the required knowledge and skill here comes from established communication or clinical reasoning skills, but could readily be supplemented by a few hours of AI-focused educational activity. Example learning outcomes would include the characteristics of AI listed above, the common misconception that current clinical AI products continually learn from patient data and the ability to explain the broad rationale underlying clinical AI use.

Beyond this universal requirement for a foundational understanding of clinical AI, **most clinicians** can expect to directly use one or more clinical AI products in their scope of practice.[9] This will require product-specific training, the provision of which is a regulatory requirement of AI medical device vendors.[16] Given the nuanced contexts and ways in which clinical AI products are deployed, it is likely to be beneficial for an institution to contribute to the design of the locally delivered training too. This training should include an operational understanding of how to use the software, much like the common induction experience that clinicians have when using new electronic healthcare records or picture archiving and communication systems. Beyond this, there should also be focused training aimed at mitigating the risks which are specific to the AI product and use case. This could be an understanding of which clinical or demographic characteristics might be considered contraindications for use, or how errors may present in the workflow. Applications of the Medical Algorithmic Audit have provided practical examples of how these mitigating learning outcomes may be derived.[17,18]

As highlighted by the 'driver' archetype of the workforce report, **some clinicians** will also be required to set the vision of AI transformation, advocate for clinical needs and risks and convene the expertise required for safe, effective and equitable care across the full AI lifecycle.[9] These individuals require 'T-shaped' expertise with deep clinical expertise relevant to the intended use of a given AI medical device and broad literacy across operational and technical issues. These clinical champions are particularly critical because their work, and therefore their educational needs, typically begins at least 2 years before an AI-enabled care pathway goes live. Inspiring, training and freeing up this workforce to perform these tasks are therefore a rate-limiting step for AI innovation in the NHS. Early clinical champions in the NHS have emerged from established clinical academic career paths and nascent fellowship schemes such as the Topol Fellowship and Faculty of Clinical AI. If the vision for hundreds of AI-enabled care pathways across all clinical specialties is to be realised, these training opportunities will need to grow in anticipation of the desired scale of AI implementation. The need for deep use case-specific expertise appears to fall outside of the scope of existing NHS career structures in clinical informatics. So far, the governance of other digital health technologies has not often required such deep clinical domain expertise, and so a general clinical background has been perfectly sufficient. A wider workforce of multidisciplinary clinical champions appears to complement existing clinical informatics roles to present a solution to the need for capacity and clinical domain expertise that will come with institution-level AI governance.

Conclusion

Successful implementation of AI in medical education is essential to meet the requirements of AI in healthcare. To achieve this, actionable guidance for a wide community of educationalists and the upscaling of training programmes for clinical champions appear as priorities for system-level intervention. In the meanwhile, individuals and institutions can draw on the principles and literature shared here to shape more immediate efforts to unlock the potential of clinical AI in the NHS.

Declaration of competing interest

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CRediT authorship contribution statement

Rohan Misra: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pearse A. Keane:** Writing – review & editing, Validation, Supervision, Conceptualization. **Henry David Jeffry Hogg:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Data curation, Conceptualization.

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