

Editorial

Artificial Intelligence in Medicine: From a Clinical Tool to a Management Challenge

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Artificial intelligence (AI) has transcended from a subject of academic curiosity to a pressing reality for hospitals around the world. At this moment, hospitals are purchasing, piloting, or implementing algorithms aiding in image analysis, patient risk stratification, documentation of clinical notes, support of remote patient monitoring, facilitation of triage, and streamlining of administrative tasks. The challenge for hospitals now is not simply whether an AI can perform a task, but rather whether a healthcare organization can integrate AI into actual clinical practice safely, transparently, and equitably.

From a hospital management perspective, AI is an issue of governance which connects procurement with clinical safety and security, data privacy and cybersecurity, training and workforce development, legal liability, and public confidence. If hospitals believe that AI is a ‘plug and play’ system, they are far more likely to develop unmanageable ‘patchwork’ systems with uncharacterized risk. Conversely, the vision that AI is an integral component of the hospital’s clinical infrastructure is more likely to unlock the potential of the technology.

1. Potential Clinical and Operational Benefits of AI

AI tools are promising in medicine. AI applications can analyze medical images, electrocardiograms (ECGs), and other signals, sometimes in vast numbers, while machine learning (ML) models can potentially identify high-risk patients who are prone to deterioration, hospital readmission, or mortality. Within the clinical workflow, AI may automate referral triage, the prioritization of the waiting list, discharge planning, and clinical documentation. Such capabilities are extremely attractive for two of the most binding constraints faced by hospitals: demand, and the need for resource allocation.

A key illustration of this initiative in the UK is the National Institute for Health and Care Excellence review of AI-based software for suspected lung cancer pathways by analysis of chest X-rays, and an emphasis on gathering evidence on performance after initial deployment. The National Health Service’s AI Diagnostic Fund is another illustration that has largely supported decision support and imaging applications, as they can impact earlier diagnoses

and waiting times [1,2]. Internationally, the Food and Drug Administration has recognized AI and ML’s potential for gaining insights into healthcare data, but also emphasized that these systems must be effectively managed from development to use and beyond [3].

Evidence is starting to shift away from purely retrospective validation and toward prospective and randomized studies. However, it is also important to ensure trials use AI-specific standards such as Consolidated Standards of Reporting Trials (CONSORT)-AI, which demand that AI components are fully disclosed, including their input data, interaction with humans, the integration within clinical workflow, error handling, and reporting [4,5]. For example, in a pragmatic randomized clinical trial of AI-supported alerts from ECG in hospitalized patients, it was shown that there was a reduced 90-day all-cause mortality in patients in the intervention group compared to controls [6]. These types of studies are critical, as hospitals require evidence on clinical utility, not solely performance accuracy.

2. Challenges in Clinical Implementation

Despite hype and enthusiasm around AI in healthcare, many AI tools fail to progress from proof of concept to routinely implemented practice. Most of the time, it is not an algorithm failure. The reasons for lack of implementation are almost always organizational, in cases where the tool does not fit the workflow, adds alert fatigue, automates processes already carried out by staff, does not interact with the electronic health records, or transfers responsibility without defining it clearly, just to provide a few examples.

Procurement is therefore not synonymous with implementation, as buying an AI does not ensure that clinicians will trust or use it, or that patients will accept the input, and that the data flows will be reliable and outcomes will improve. A hospital can buy a high-performing algorithm and still have a less than effective system due to underlying deficiencies in other areas of the infrastructure. However, even a lesser-performing algorithm may provide clinical value if it solves a well-defined problem, is integrated safely into the clinical workflow, and is continually monitored and auditable.



It is this distinction between procurement and implementation that makes AI an issue that impacts every part of the organization and, thus, represents a challenge of clinical governance, as these tools change workflows, affect who is alerted and why, are involved in how uncertainty is documented, and, ultimately, can determine accountability.

3. The Need for Institutional Governance

The foundation for any successful implementation of AI in hospitals must be an effective AI governance structure. A governance structure should, at a minimum, outline procedures for maintaining an institutional register of all AI applications used within the organization, classifications of risk, mechanisms for assessing clinical safety, procedures for data protection, clear procurement guidelines, guidelines for staff training, patient communication policies, and mechanisms for continued performance monitoring and reporting. Formalized and objective evaluation before larger-scale adoption must be standard. Frameworks such as Developmental and Exploratory Clinical Investigations of Decision support systems driven by Artificial Intelligence (DECIDE-AI) can provide assistance as they help evaluate the real-world effectiveness of AI-based decision support systems with a focus on their intended use, the interaction with humans, the workflow, the types of errors that occur, and the context of use [7].

The WHO has identified transparency, responsibility, accountability, inclusiveness, equity, and sustainable responsiveness as principles guiding the use of AI in health [8], and has also identified risks for large multimodal models (e.g., bias, misinformational risk, automation bias, cybersecurity, inequitable access), while also outlining opportunities in diagnosis, communication, clerical work, research, and education [9].

The EU's AI Act classifies most of the high-risk medical applications, mandating clear processes for risk management, the use of high-quality datasets, transparency with the user, and human oversight [10]. In the UK, the Medicines and Healthcare products Regulatory Agency (MHRA) has defined guidance on AI as a medical device and the MHRA's AI Airlock scheme aims to evaluate and reduce regulatory challenges related to AI medical devices in a real-world setting [11,12]. Therefore, local governance models must complement these regulations.

4. Bias, Model Drift and Equity Considerations

AI can appear objective, producing scores or recommendations, but this is an illusion, as these systems learn from historical data, which represents systemic inequalities, gaps, and operational patterns of care. For example, the widely-cited study by Obermeyer et al. [13] revealed racial bias in health-management algorithm performance, using cost as a proxy for health need, resulting in lower predicted risks for Black patients compared to White patients.

It is important not to overlook data drift, where a model's performance degrades over time due to changing populations, practice patterns, coding, or equipment [14], and where data reflects these changes, hospitals should monitor for this drift through regular auditing, sub-analysis of data, and defining criteria for action when drift is detected.

Equity must not be a second thought, but a first implementation priority, and the Standards for data Diversity, Inclusivity, & Generalisability (STANDING) Together guidelines emphasize the need for transparent data governance, including a detailed description of datasets used, their limitations, and generalizability [15]. Vendors should be able to provide evidence not only of overall performance but also of subgroup performance.

5. Clinical Oversight and Professional Accountability

Clinicians must always retain control of AI systems. As such, hospitals must also create training programs for clinical staff about the limitations of AI and how they can interpret its recommendations. It is not enough for every clinician to be able to code; they must be able to trust and critically evaluate AI output and communicate their role to the patient appropriately.

A safe approach to AI requires awareness of new potential types of error, such as automation bias (where a human is prone to accept a computer-generated output as correct, even if it seems improbable) or automation neglect (where a user doesn't monitor and use AI tools, failing to exploit their benefits). Hospital-based AI training must focus on real-world tasks, such as where the AI is applied, what action to take, how to deal with uncertainty, and what to do if a clinician disagrees with the AI.

6. Strategic Considerations for Hospital Leadership

AI use in hospitals cannot be left to isolated innovation teams. The board should always question the role of AI and consider the following issues before its adoption: Why is this tool needed? What is the evidence that it improves important outcomes? How will the technology fit into the existing workflow? What is the risk to patients, staff, and data security? How will performance be monitored post-implementation? Who is responsible if harm results from its use? How and what will patients be informed about its use?

These questions will often have clinical, managerial, and ethical aspects, and must be a collaborative effort involving front-line staff, hospital leadership, digital departments, information governance, legal teams, patients, and procurement departments. Ultimately, the safest hospitals may not necessarily use the most AI but be those with the most robust AI governance.

7. Conclusion

AI will play a key role within modern healthcare, but successful integration will be more about how AI is used than about the complexity of the algorithm itself. Performance effectiveness within a controlled setting is not equivalent to safety within a ward, and regulatory approval is not synonymous with hospital readiness.

A vendor demonstration is not synonymous with clinical utility, and an obligation to maintain safe and responsible AI demands that organizations move beyond initial enthusiasm towards active stewardship. Selecting AI that addresses a real need, integrating it into safe workflows, training staff to use it, monitoring performance and creating clear lines of accountability are important. For AI to be successful in medicine, greater innovation may be needed within hospital systems to establish effective AI governance.

Key Points

- AI in medicine is moving from experimental promise to practical hospital deployment.
- Hospital leaders must evaluate AI for workflow fit, safety, accountability, cybersecurity and equity, not only accuracy.
- Procurement without governance risks creating fragmented, unsafe or unused digital tools.
- Clinicians require training to understand AI outputs, limitations and automation bias.
- Responsible AI adoption requires continuous monitoring, audit, incident reporting and clear institutional accountability.
- The future of AI in medicine depends on hospital-level governance as much as algorithmic performance.

Availability of Data and Materials

Not applicable.

Author Contributions

SD, DGN, and CS designed, drafted, and reviewed the manuscript. All authors contributed to important editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

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Conflicts of Interest

The authors declare no conflicts of interest.

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