



The final biological component: AI and radiology's mechanistic drift

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Artificial intelligence (AI) in radiology is often described as an external technological force: algorithms that detect nodules, triage hemorrhage, quantify liver fat, or classify mammographic abnormalities. The prevailing debate therefore centres on replacement versus augmentation. Yet this framing may obscure a quieter and potentially more consequential transformation. The greater risk may not be that AI replaces radiologists from outside the profession, but that radiologists gradually adapt themselves—and their professional environment—toward forms of practice increasingly aligned with the operational logic of machine systems. Importantly, this process did not begin with deep learning or the recent AI boom. It has been underway for decades, driven by productivity metrics, standardisation protocols, and medicolegal pressures. AI then accelerates and deepens an existing drift rather than initiating it.

Radiology has always occupied a complex position between technical analysis and clinical interpretation. Imaging interpretation involves pattern recognition, but it also requires contextual integration: weighing findings against clinical history, communicating uncertainty, integrating temporal change, and understanding the implications of a report for a particular patient. As Osler¹ observed more broadly in medicine, scientific generalisation must ultimately return to the care of singular individuals.

The concern developed here is therefore not directed against AI itself. Many AI systems demonstrably improve efficiency, reduce repetitive workload, and may enhance diagnostic performance in selected domains. Nor is standardisation inherently problematic; structured reporting, evidence-based imaging pathways, and protocol harmonisation have often improved consistency, communication, and patient safety. Rather, the concern is that existing institutional pressures—including productivity metrics, medicolegal anxieties, and workflow optimisation—may increasingly privilege those dimensions of radiological work that are easiest to standardise, quantify, and computationally integrate. This editorial refers to this process as *mechanistic drift*: the gradual reorientation of professional identity toward machine-compatible modes of practice. The phenomenon predates contemporary AI and reflects broader industrial tendencies within modern medicine. AI amplifies these tendencies not because the technology is intrinsically dehumanising, but because computational systems naturally reward tasks that are measurable, reproducible, and scalable.

Mechanistic drift

Contemporary radiology operates under substantial structural pressure. Relative value unit–based reimbursement systems, productivity metrics, turnaround-time expectations, and protocol standardisation have improved throughput and consistency across many healthcare systems. These developments have undeniable practical value. Yet they may also produce secondary epistemic effects by privileging aspects of practice that are easiest to count and operationalise.

Activities such as rapid image interpretation, standardised reporting, and protocol adherence are readily measurable. Other dimensions of radiological expertise—including reflective deliberation, extensive clinical correlation, communication with referring physicians, or nuanced contextual reasoning—are more difficult to quantify within institutional systems.



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Over time, this imbalance may subtly influence what becomes recognised as professional excellence. Crucially, this imbalance existed long before AI entered clinical radiology. The introduction of AI merely intensifies an already established tendency: if a task can be measured, it can be optimised; if it can be optimised, it can be automated.

Clinical decision support systems illustrate this tension. Such systems were developed to improve appropriateness and reduce unnecessary imaging rather than to create “cookbook medicine.” Nevertheless, implementation within high-volume environments may unintentionally encourage guideline adherence to function as a surrogate marker for quality itself.² Similarly, AI systems designed for detection support may gradually shape expectations regarding efficiency, concordance, and acceptable interpretive variability.

The concern is therefore not that radiologists use AI tools, but that radiological cognition itself may increasingly adapt toward machine-compatible priorities. Pattern recognition, protocol recall, rapid triage, and workflow acceleration are valuable capacities. However, when these capacities become dominant markers of competence, other forms of judgment risk becoming institutionally secondary. Human beings, not algorithms, are the ones who progressively redesign their own professional territory to resemble the conditions under which machines excel.

Research on automation bias demonstrates that clinicians may overaccept automated recommendations, particularly under conditions of cognitive load and workflow pressure.^{3,4} Existing literature does not establish that AI erodes professional identity directly. However, it does suggest that workflow environments can influence how human judgment is exercised, deferred, or verified. The present concern is therefore sociotechnical rather than deterministic: institutional systems may progressively incentivise narrower forms of practice without any explicit intention to do so, and this tendency has been reinforced by successive waves of computational technology—not only by contemporary AI.

H-knowledge and I-knowledge

To clarify the epistemic stakes of mechanistic drift, this editorial proposes a heuristic distinction between two poles of professional knowledge. These categories are analytic rather than binary; most radiological practice contains elements of both.

H-knowledge (Human/Relational knowledge) refers to forms of understanding grounded in contextual interpretation, embodied experience, and moral answerability. In radiology, H-knowledge includes integrating imaging findings with the patient’s clinical narrative, recognising subtle contextual discordances, communicating uncertainty responsibly, and appreciating the downstream consequences of interpretation. It includes tacit dimensions of expertise that are difficult to formalise completely within algorithmic systems. This conception draws partly from phenomenological traditions associated with Merleau-Ponty,⁵ in which perception is not treated as passive data acquisition but as embodied and situated interpretation. H-knowledge also resembles *phronesis*, or practical wisdom: the capacity to integrate technical knowledge with situational judgment under conditions of uncertainty.⁶

I-knowledge (Information/Digital knowledge) refers to forms of knowledge structured for abstraction, scalability, standardisation, and computational manipulation. In radiology, this includes labelled imaging datasets, probabilistic classification systems, standardised reporting structures, and algorithmically optimised workflows. I-knowledge is extraordinarily powerful precisely because it permits reproducibility, scalability, and pattern detection beyond unaided human capacity.

The distinction should not be interpreted as a moral hierarchy. Human cognition itself depends heavily on abstraction and probabilistic reasoning, while advanced computational systems increasingly incorporate multimodal contextual information. The concern is therefore not abstraction per se, but the possibility that institutional systems may progressively privilege I-oriented competencies while rendering H-oriented competencies less visible, less rewarded, or less cultivable. If that occurs, professional identity may gradually shift toward narrower definitions of expertise centred primarily on efficiency, concordance, and standardisation. Such a shift would not eliminate human radiologists, but it could reduce the practical space within which reflective judgment and contextual interpretation operate.

Answerability

The concept most vulnerable within mechanistic drift may be *answerability*. By answerability, this essay refers not simply to legal accountability or procedural compli-

ance, but to the lived moral exposure associated with diagnostic judgment.

Radiological reports guide surgery, chemotherapy, surveillance, reassurance, and prognostic expectation. A missed finding or overcalled abnormality may alter the course of a patient’s life. Human clinicians experience these consequences psychologically and ethically even when they satisfy formal procedural requirements. This differs fundamentally from computational systems, which may participate causally in clinical outcomes but do not themselves experience moral consequence.

The distinction between accountability and answerability is therefore important. Accountability may be satisfied through compliance with guidelines or institutional workflow. Answerability involves a deeper phenomenological dimension: the recognition that one’s judgment has affected another person. A radiologist may follow every procedural expectation correctly yet still experience profound distress after a missed diagnosis. Conversely, a technically compliant system may generate harmful outcomes without any lived experience of responsibility.

The “second victim” phenomenon illustrates this dimension of medical practice.⁷ Radiologists who miss consequential findings may experience guilt, anxiety, shame, and long-lasting professional self-doubt. Such reactions are painful but also reveal that diagnostic interpretation remains *morally inhabited* rather than merely procedurally executed.

At the same time, the desire to minimise personal exposure to error may paradoxically reinforce mechanistic practice. Under medicolegal pressure, radiologists may increasingly rely on protocol adherence, guideline conformity, or algorithmic concordance as forms of defensive protection. This tendency does not arise from moral failure but from understandable adaptation to institutional environments that reward standardisation and penalise deviation. Preserving answerability does not require rejecting technological assistance. Rather, it requires maintaining active interpretive engagement. Brief but meaningful practices—reviewing the clinical history carefully, comparing prior examinations, communicating uncertainty directly, or discussing unexpected findings with referring clinicians—help preserve the relational grounding of radiological work even within technologically advanced systems.

Structural incentives and professional adaptation

Mechanistic drift should not be understood primarily as an individual cognitive failure. It is better interpreted as an adaptive response to broader structural incentives embedded within healthcare systems. Moreover, these incentives have operated for decades, long before the recent proliferation of AI.

Reimbursement models often reward volume more directly than reflective consultation. Medicolegal frameworks may discourage deviation from standardised pathways even when contextual judgment suggests nuance. Commercial AI systems are frequently evaluated according to measurable performance metrics such as sensitivity, specificity, throughput improvement, or workflow acceleration rather than according to their effects on professional reasoning.

Institutionally, standardised error may also be perceived differently from individual deviation. A radiologist who follows an accepted algorithmic recommendation may be viewed as participating in a system-level failure, whereas independent deviation from protocol may attract greater scrutiny even when clinically justified. Over time, such asymmetries may subtly shape professional behaviour.

Yet it would be mistaken to frame this process as inevitable technological determinism. Professional cultures retain agency in deciding what forms of expertise they choose to value, reward, and teach. The future role of radiologists will depend not only on algorithmic capability, but also on how institutions define clinical excellence itself.

Preserving radiological judgment

Preserving radiological judgment does not require resisting AI wholesale. The challenge is to integrate computational systems in ways that support rather than displace active interpretation.

For practicing radiologists, one practical strategy is to formulate an independent preliminary assessment before reviewing algorithmic output whenever feasible. Explicit documentation of why a guideline or AI recommendation was overridden may also help preserve reflective reasoning rather than passive concordance.

For educators, training environments should ensure that residents continue developing unaided interpretive skills and contextual clinical reasoning. Cases in which AI systems fail, oversimplify, or misclassify findings should be discussed not merely as technical errors, but as opportunities to examine the limits of computational abstraction.

For institutions, workflow architecture matters. Systems could be designed to encourage active preliminary interpretation before AI output becomes visible. Time protected for discrepancy review, multidisciplinary discussion, and reflective quality forums may help preserve the moral and interpretive dimensions of radiological practice.⁸ Importantly, such measures should not romanticise individual intuition at the expense of evidence-based medicine, but rather maintain a productive balance between computational support and professional judgment.

The goal is therefore not to preserve radiology as an artisanal resistance movement against technology. It is to ensure that efficiency and standardisation do not become the sole visible markers of expertise.

Radiology's mechanistic evolution has produced extraordinary gains in speed, consistency, accessibility, and diagnostic capability. AI will almost certainly deepen many of these advances. Yet when optimisation becomes the dominant organising principle of professional identity, radiology risks narrowing its own conception of expertise.

The central question is not whether AI will eliminate radiologists entirely. Human clinicians remain indispensable for contextual interpretation, communication, procedural care, multidisciplinary integration, and ethical responsibility. The more important question is whether radiological authority may gradually compress into increasingly standardised and machine-compatible forms of practice. Because this compression is driven not by AI invading human territory, but by humans rendering their own territory ever more AI-like—a process well underway before the current wave of AI—the profession retains the capacity to reverse or moderate it.

Radiology is not defined solely by image classification accuracy. At its best, it remains an interpretive discipline in which technical perception is integrated with contextual un-

derstanding and moral responsibility. If these dimensions become secondary to workflow optimisation and algorithmic concordance, the radiologist risks becoming the *final biological component* within the imaging system: a human presence retained less for independent judgment than for procedural ratification, legitimising decisions increasingly shaped elsewhere.

The future of radiology therefore depends not only on what AI can do, but on what forms of judgment the profession continues to cultivate, reward, and defend.

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