

Skill Erosion and Identity Shifts Under AI Delegation in Imaging-based Medicine

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Abstract

This paper reports on a qualitative study with 12 experts across dermatology and radiology about the risk of AI-induced skill erosion. Integrating AI tools (e.g., visual diagnosis, generative scribes) into medical workflows introduces the risk of AI-induced skill erosion among experts despite short-term efficiency gains. While existing literature focuses on short-term behavioral phenomena like automation bias and real-time accuracy, it fails to capture how continuous AI integration alters what clinicians consider essential skills and reshapes professional identity over time. We conducted 12 semi-structured interviews and speculative design workbook activities with expert radiologists and dermatologists. From this study, we derived the Human-AI Clinical Skill Framework, which maps how modular, unitary, and dynamic skill philosophies intersect with mechanical, integrative, and translational skill tiers, and what it means for clinical expertise in an AI-powered practice. We conclude with design principles for integrating AI into medical tools to mitigate skill erosion.

CCS Concepts

• **Human-centered computing** → **HCI theory, concepts and models**; *Empirical studies in HCI*; Scenario-based design.

Keywords

Artificial intelligence, skill erosion, medicine, design

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1 Introduction

As artificial intelligence (AI) systems are rapidly transforming professional practice in various fields of knowledge work, decision-making is increasingly supported by AI models. Research suggests that AI-driven decision aids, combined with the organisational goals that prioritise efficiency, often encourage over-reliance, inhibiting up-skilling in domain-specific knowledge and skills, critical thinking, and decision-making [23]. As deep, tacit knowledge erodes, organisations lose the capacity to diagnose and resolve unexpected problems, such as when AI systems fail or encounter novel conditions. These risks are already evident. In medicine, research has shown that endoscopists eroded diagnostic ability after just a few months of use of an AI decision aid, as they become over-reliant on AI and experience a phenomenon called AI-induced skill erosion (also called de-skilling in participants' quotes in Section 4) [3, 17]. Though this practice may produce short-term performance gains, the long-term, individual, and organisational performance will drop with the loss of expert's knowledge and skills at an institutional level [21]. In particular, medical diagnosis represents a high-stakes context where AI-assisted decision-making has significant ethical and professional implications [24]. Errors can directly affect patients' wellbeing and may carry legal and regulatory consequences [12], which makes questions of oversight, skill retention, and appropriate reliance on AI particularly critical.

Existing human-AI interaction and medical AI literature predominantly examines AI integration as a static, point-in-time decision challenge, focusing heavily on short-term behavioral phenomena such as automation bias [1], trust calibration [22], and verification accuracy during real-time decision-making [25]. While these inquiries offer valuable insights into how clinicians evaluate AI predictions, they do not capture how clinicians anticipate the longitudinal effect of AI adoption on clinicians, specifically what skills clinicians see as essential, the conditions for which certain tasks can be delegated to AI, and how AI affects the clinicians' concept of skills and professional identities.

Our study addresses these problems under the main research question: How should we conceptualize and assess skill erosion and skill development that clinicians experience when working with AI? We focused on dermatology and radiology, as imaging-based diagnosis is one of the prominent areas for AI assistance. Our study consists of semi-structured interviews and speculative design workbook activity with 12 dermatologists and radiologists. From this, we

derived the Human-AI Clinical Skill framework, which maps the structural interactions between three clinical task tiers (mechanical, integrative, and translational) and three clinician skill philosophies (modular, unitary, and dynamic). This framework highlights the interaction between clinician's perspectives on AI, factors for task delegation, and values related to professional skills and identities. Building on this framework, we discuss how various system design strategies may mitigate medical skill erosion in the age of AI.

2 Literature Review

2.1 AI decision support systems in medicine

Artificial intelligence (AI) decision support systems have rapidly advanced across imaging-based medical fields, including dermatology and radiology [6]. Modern clinical AI tools typically employ deep neural networks to assist clinicians through automated image classification, lesion segmentation, and screening triage [9]. Human-Computer Interaction (HCI) research in healthcare has extensively studied the integration of these models, primarily emphasizing interface design paradigms that facilitate trust calibration, explainability, and AI's transparency [4]. However, prevailing HCI and medical AI paradigms predominantly conceptualize AI adoption as a static deployment rather than how longitudinal system usage can dynamically alter conceptualization and evaluation of clinical skills [15].

2.2 Overreliance and professional skill erosion

A central concern in human-AI interaction is the skill erosion, especially reasoning and decision-making skills, after prolonged usage of automated decision support. Some behavioral indicators of this phenomenon include automation bias and overreliance [20]. Under heavy workloads, individuals naturally seek operational efficiency and relief from fatigue, leading clinicians to become negligent in overseeing AI, instead approving AI suggestions without proper verifications [1]. Furthermore, literature on skill acquisition shows that prematurely delegating foundational execution tasks to automated systems impedes the development of intuitive expertise, a phenomenon empirically documented in aviation [5] and as well as dermatology [8]. Notably, both fields rely on processing extensive volumes of routine screening cases to build baseline visual pattern recognition and intuition, highlighting the concern of AI-integrated training systems in similar fields. Our study builds upon the literature by introducing a holistic and normative framework that connects task-level delegation and automation bias to long-term professional skill erosion and identity transformation. By mapping how different tiers of skills interact with clinicians' underlying skill philosophies, we provide a structured way to discuss the impact of AI on healthcare workflows and design implications that mitigate AI-induced erosion of human expert's essential skills.

3 Method

To answer our research question, we conducted a qualitative empirical study combining semi-structured interviews with speculative design workbook activities. We selected dermatology and radiology as our primary contexts because both domains involved imaging-based pattern recognition, making them early adopters of AI-powered diagnostic systems. This approach lets us ground the

study in present workflows while pushing participants beyond current technology limitations to pinpoint their comfort boundaries, mental models, and professional values around AI integration [10].

3.1 Participants

We recruited 12 medical professionals (6 dermatologists and 6 radiologists) through purposeful sampling and professional network snowballing. Inclusion criteria required participants to be at least 19 years old, hold an active medical license or residency appointment in dermatology or radiology, and actively engage in imaging-based diagnosis as part of their routine practice. The participant pool was balanced across career stages, ranging from trainees/residents to senior professors, across six countries (Australia, USA, Canada, Germany, Italy, UK), offering diverse views on training systems and professional code of conduct. Participant familiarity with AI was categorized qualitatively based on self-reported clinical and research experience, spanning a spectrum from daily clinical use of commercial software to trial- or research-only exposure influenced by differing national regulatory frameworks.

3.2 Procedure

Data collection was structured into two parts, conducted remotely in one 60-minute session. Both parts were conducted individually.

Part 1—Semi-structured interview: This part explored real-world clinical workflows, time distribution, and mental effort across tasks. To ground reflections in lived practice rather than abstract speculation, participants walked through recent standard versus complex diagnostic cases (e.g., "Which parts feel most meaningful or professionally satisfying?"). We probed participants' explicit conceptions of clinical competence (e.g., "How do you tell if someone is a good dermatologist/radiologist?") and the factors governing accountability and error management in imaging workflows (e.g., "What is the consequence you would face for missing or providing an incorrect diagnosis?"). For participants with prior exposure to clinical AI decision support, we explored how these tools impacted their performance and perceived skill trajectories.

Part 2—Speculative design workbook activities: Participants engaged in a two-part speculative design activity designed to push their boundaries around AI task delegation and evaluate how different interface interactions shape cognitive engagement:

- (1) *Compare-and-contrast interaction paradigms:* Participants were introduced to two contrasting diagnostic interface paradigms. The *Recommendation-First* layout immediately presents AI predictions, confidence scores, and suggested clinical actions upon opening a study. The *Cognition-First* layout requires the clinician to input their independent diagnosis first before revealing AI assessments. Participants discussed suitable tasks, required operator skills, and performance thresholds for each interaction mode.
- (2) *Boundary-finding scenarios:* We presented three scenarios, and asked participants to reflect on how these scenarios align with their values, cognitive process, and responsibilities, and how delegation to extreme use of AI in different parts of the work may affect their skills and professional code of conduct. The scenarios were:

- **Case filtering based on AI's diagnosis confidence:** AI independently flags and filters high-confidence cases (e.g., >95% confidence) so they never reach human expert eyes, though humans can audit. This scenario focuses on autonomy, accountability, and authority.
- **Autonomous biopsy scheduling:** AI automatically schedules biopsies, generates pre-operative instructions, and updates system records upon detecting high-risk conditions, leaving clinicians to override asynchronously. This scenario focuses on accountability, workload, and integration into workflow.
- **AI-generated referrals:** AI automatically generates and sends referral letters to specialist departments (e.g., Oncology) or back to the general physician following human-AI joint diagnosis, with the clinician CC'ed. This scenario focuses on professional communication and reputation.

3.3 Data Analysis

Audio recordings were transcribed verbatim and analyzed following an inductive-to-deductive thematic analysis approach [2].

- **Inductive Analysis:** The primary researcher performed in-vivo open coding on raw transcripts to preserve natural clinical vocabulary surrounding workflow, cognitive burden, and identity. Through regular iterative team debriefs, initial codes were grouped into broader thematic clusters reflecting clinical skill types and delegation attitudes. From these clusters, we derived the core 3×3 matrix structuring our framework.
- **Deductive Analysis:** The research team applied a deductive coding pass to populate the matrix cells across all transcripts. Crucially, our analysis revealed that the three skill philosophies (modular, unitary, dynamic) do not represent rigid, mutually exclusive clinician personality types. Rather, an individual clinician may adopt fluid philosophical positions depending on task context, risk tier, or professional role. For instance, participants frequently held a Unitary stance when supervising trainees or evaluating high-stakes diagnostic edge cases—insisting on unassisted human reasoning—yet shifted toward a Modular or Dynamic stance when executing routine administrative tasks or personal high-volume screening.

4 Findings

4.1 Human-AI Clinical Skill Conceptual Framework

To synthesize how varying degrees of AI decision support influence clinical competence, we developed the Human-AI Clinical Skill framework, which maps three Skill Philosophies against three Tiers of Clinical Skills. The three skill philosophies are:

- (1) The *unitary philosophy* conceives expertise as an indivisible and tightly integrated capability, where delegating any components to AI risks eroding essential skills.
- (2) The *modular philosophy* views clinical competence as a set of discrete, separable tasks that can be individually automated

or delegated without altering the integrity of the remaining process.

- (3) The *dynamic philosophy* conceptualizes clinical competence as adaptive and evolving, with clinician expertise continuously shifting to focus on patient-facing, empathic interactions as AI becomes increasingly integrated into their workflow.

The skill tiers which interact with these philosophies include:

- (1) The *mechanical tier* encompasses foundational, rule-based perception and execution, such as imaging-based measurements, surface pattern recognition, and automated template population.
- (2) The *integrative tier* involves synthesizing multi-modal clinical evidence, contextualizing diagnostic probabilities within patient histories, and evaluating differential diagnoses.
- (3) The *translational tier* addresses high-order interpersonal communication, patient care, and navigating ethical complexities.

Table 1 maps the skill philosophies across the three skill tiers, illustrating the resulting human-AI interaction dynamics and potential consequences on clinical skills. For the rest of this section, we will illustrate each part of this framework in more detail. We use the subscript letter D and R after the participant's number to label them as dermatologist or radiologist, respectively.

4.2 The Unitary Philosophy

Under a *unitary* skill philosophy, clinicians view diagnostic synthesis as a holistic cognitive process, arguing that AI must function strictly as a post-hoc “second opinion” rather than a primary decision aid. Presenting AI recommendations upfront induces automation bias because “I already know a hypothesis. So the bias would be that I start by considering this hypothesis.” (P4_D) This is especially important because of how AI results are often interpreted: “If we see AI scores which are high, then we have the tendency to worry.” (P8_D) Notably, this form of AI integration prioritizes diagnostic accuracy over workflow speed. Because both human intuition and AI models are fallible, AI can provide a safety net: “I think it's better if you use it all the time. Even with a clear diagnosis, even if you are sure.” (P1_D)

While systems often prioritize efficiency gains, the *unitary* philosophy dictates that clinicians must actively resist cognitive offloading to preserve core competencies. Because final legal and ethical liability rests on human clinicians, experts view continuous skill retention as a part of their responsibilities, both for exercising independent judgment and supervising AI. P3_R noted: “In terms of making diagnoses and final recommendations, there should be a human involved. Just because if there is something that goes wrong, at least there was a human”. This perspective contrasts with the views that frame the physician's role as dynamically evolving, which will be illustrated more in Section 4.4.

4.3 The Modular Philosophy

4.3.1 Experiencing low case volumes hinders trainees' upskilling. Offloading low-risk, routine tasks, such as image filtering or basic measurements of features in the scans, can help improve the efficiency and comprehensiveness of the workflow, as AI can be

Table 1: The Human-AI Clinical Skill Matrix: Each cell describes the cognitive and professional challenges and considerations around delegation to AI arising from the interaction between each skill tier and each skill philosophy

Skill Tiers	Unitary Philosophy	Modular Philosophy	Dynamic Philosophy
Mechanical Tier (e.g., <i>surface pattern recognition, image filtering, initial triage</i>)	Mechanical skills are a necessary foundation to develop skills in higher tiers (4.2)	Mechanical tiers are non-essential, but delegating them makes trainees lack practice case volume necessary for developing clinical intuition (4.3.1)	Philosophical non-issue (4.4)
Integrative Tier (e.g., <i>diagnostic synthesis, contextualizing evidence, differential generation</i>)	AI should only be utilized as a “second opinion” in integrative tasks (4.2)	Experts risk skill erosion in the integrative tier as workload pressure increases (4.3.3)	Philosophical non-issue (4.4)
Translational Tier (e.g., <i>patient communication, shared decision-making, ethical navigation</i>)	Translation tasks should be retained for humans due to legal and ethical liability to patients (4.2)	Experts risk becoming passive and less cognitively involved in overseeing AI for translational tasks (4.3.2)	Identity of healthcare providers may need reframing to focus mainly on translational skills (4.4)

more thorough in these tasks than clinicians under fatigue ($P7_R$). However, participants expressed concern that introducing it early in the training process may create a critical blockage for early-career clinicians, who rely on high case volumes to build clinical intuitions and knowledge bases necessary for higher-level skills, such as image filtering skills: “Once you learned it, it’s a boring skill, but you have to learn it to focus on the interesting cases later on” ($P12_R$). Similarly, delegating simple and obvious cases to AI could be detrimental, as “you need the normal cases to get a feeling for the complex and bad cases, so that ultimately connects to each other” ($P6_R$). Thus, while *modular* task delegation promises efficiency, applying it during training may inhibit upskilling, making trainees unable to step in when the cases are too difficult to delegate to AI.

4.3.2 Potential traps around AI-assisted communication. Clinicians who adopt a *modular* skill philosophy toward communication (e.g., writing referral letters and diagnosis reports) view text generation and narrative construction as isolated from diagnostic reasoning. However, participants cautioned that treating communication as a separate block may create cognitive passivity, introducing systemic risks of poor integration of knowledge during diagnosis, referral, and other steps in the medical workflow. $P11_D$ supports this with her reflection on using the AI medical scribe: “I don’t have to listen to every word and process it straight away. And I might lose [information] reorganization skills because the AI is doing that for me.” Here, the participant highlights how offloading real-time listening can also affect information processing at a deeper level. Participants were concerned that such passivity could lead to clinicians gradually signing off on automated text without rigorous oversight and expose clinicians to “legal problems” and “a sense of stolen identity” ($P2_D$) when clinical documentation no longer reflects the physician’s voice or judgment in full.

4.3.3 Working with AI requires experts to upskill in AI literacy. Participants noted that, when delegating some work to AI in the *integrative* tiers, expert oversight will require deep AI literacy to resist the pressure of workload and fatigue. As AI gets better, clinicians with a *modular* philosophy would consider: “If I’m a lazy guy, I will tend to upload the whole stack of images and just go with whatever the AI will tell me. And I will soon maybe not check twice” ($P12_R$). Effective oversight therefore requires experts to know “what are the risks, or why you may not trust those results [...] how they are trained” ($P1_D$). Crucially, experts must develop an understanding of how AI errors differ fundamentally from human mistakes, necessitating different auditing strategies than traditional peer review when delegating the same work to a human colleague, as $P10_D$ noted: “With a colleague, I don’t feel like I need to check the work of human colleagues, who I consider more or less comparably competent as me. But if there was an AI that was similarly competent to me in terms of the statistical parameters, the sensitivity and specificity or whatever, are the kinds of mistakes the same?” This shows that modularly delegating work to AI requires redefining the tasks and developing new skills.

4.4 The Dynamic Philosophy

Clinicians embodying the *dynamic* philosophy view clinical expertise as an evolving, adaptive partnership with automated systems. Under this perspective, potential skill loss across *mechanical* and *integrative* tiers is largely viewed as a philosophical non-issue. Senior clinicians describe historical skill erosion as a routine, acceptable trade-off of technological progress:

“What we deem a core skill today may not be a core skill tomorrow. Things that we did 40 years ago, we don’t do today. [...] Something called an IVP—intravenous pylogram— where you would inject some dye, you’d take different types of x-rays to look at how the kidneys are functioning, are there any tumors in the

ureters and in the bladder? That test is almost unheard of. Instead, we do CT scans. Through the innovation of radiology, we've had de-skilling. So, de-skilling is not a new phenomena, as better techniques come out" (P7_R).

As diagnostic tasks migrate to machines, *dynamic* philosophy speculates that core responsibility would naturally relocate to the *translational* tier, focusing on empathetic patient communication and bridging the "large gap between medical speech and patient speech" (P12_R). They view human presence as irreplaceable: "A good and bad diagnosis should be communicated by a person, and not by a tool, by technology in general, because we are human, so we need the contact and the empathy, and the warmth, and the kindness of another person" (P2_D). However, this shift creates new concerns, as clinicians think it will force a fundamental redefinition of the healthcare provider's professional identity (P7_R). The shift also surfaces deeper questions about what a medical license signifies when algorithmic tools share the diagnostic loop: "Who is taking responsibility? What is the meaning of a medical license to practice?" (P9_R). From a *dynamic* perspective, professional adaptation requires moving beyond task-level delegation to systematically renegotiate the boundaries between human empathy, technical oversight, and clinical authority.

5 Discussion

5.1 Relating to existing literature and frameworks

The workplace dynamics identified in this study connect directly to established empirical work on clinical AI adoption. Prior research has documented how AI integration into the medical workflow can threaten professional identity [11], the necessity of redesigning curricula alongside AI integration [14], and the concern around automation bias for clinician's decision support [1]. Our Human-AI Clinical Skill framework builds upon these isolated observations by providing a unified conceptual framework. By mapping these phenomena across skill philosophies and skill tiers, we offer a structured foundation for future research on cognitive skill erosion and clinical workflow design.

Our framework also refines and extends existing AI implementation frameworks in medicine. While scoping reviews emphasize organizational adaptation and technical translation [7], our work focuses on the underlying clinician's skill philosophies and how they influence the opportunities and potential pitfalls at different skill tiers. Design frameworks establishing requirements for trustworthy healthcare AI [18] are extended by looking at AI in tasks beyond diagnosis and imagining AI support under the shifting role of healthcare providers. Finally, our framework adds to the discussion around the legal framework for AI adoption [19] by surfacing the common patterns across clinicians in various locations around the world on what constitutes clinical accountability and core competencies.

5.2 Design implications

Based on our framework, we outline three design principles for AI-integrated clinical tools to mitigate skill erosion, support evolving

medical roles, and align with clinicians' underlying skill philosophies:

- (1) **Enable specialization transitions (addressing 4.3.1 & 4.4):** As diagnostic tasks migrate to AI, systems should equip emerging specializations (e.g., technical auditor, interpersonal communicators) with the target metrics they need to guide their evolving workflow. For instance, technical auditors' interfaces should provide visibility into the model's training and analysis for accurate identification of risks and errors. As for patient communication, systems should provide visual risk translation tools, such as patient-facing vocabularies and diagrams, to help bridge the comprehension gap between complex model outputs and actionable patient dialogue.
- (2) **Prevent automation bias (addressing 4.2):** Interfaces should enforce independent clinician reasoning before displaying machine predictions to ensure that its decision is taken strictly as a "second opinion". This approach is called cognition-first in human-AI interaction literature and could be executed through various mechanisms, such as evaluative AI [13] and frictional AI [16].
- (3) **Provide proactive steps beyond oversight (addressing 4.3.2 & 4.3.3):** Under high workload pressure, interfaces should introduce targeted cognitive-forcing functions to maintain active oversight. For example, they could implement deliberate micro-delays or mandatory confirmation prompts when clinicians attempt rapid sign-offs under tight timelines. As for clinical documentation (translational tier), generative AI tools may be restricted to producing outlines rather than complete, finalized prose, forcing the clinician to actively assemble and review the final clinical report.

5.3 Limitations and Future Work

We acknowledge three methodological limitations. First, while our sample of twelve clinicians could capture domain-specific insights, it may not fully represent dynamics in non-imaging fields. Second, our investigation relied primarily on semi-structured interviews and speculative design probes, which are effective for exploring existing challenges and surfacing mental models but don't capture real-time, long-term observational data. Third, participants' prior exposure to AI was self-reported and qualitative rather than measured, so we cannot quantitatively connect their experiences and skills with their perspectives and opinions.

To address these limitations, we will design and deploy AI-integrated prototypes that have the interaction mechanisms from Section 5.2. We will then conduct a longitudinal study tracking junior clinician's skills in each tier over an extended period, aiming to give quantitative measures of cognitive skills over time.

6 Conclusion

This study addresses the critical challenge of AI-induced skill erosion in imaging-based medical practices. It introduces the Human-AI Clinical Skill framework, which connects three clinical skill tiers (mechanical, integrative, and translational) with three skill philosophies (modular, unitary, and dynamic). Our findings reveal that clinicians do not perceive skill erosion as an inevitable consequence

of AI integration, but risks occur when tasks are segmented and delegated under acute workload pressure, leading to lack of foundational intuition in trainees and passive AI oversight in experts. Beyond interface design, this work also offers novel considerations and challenges on how medical codes of conduct and legal liability frameworks should adapt as human expertise evolves in the AI-assisted healthcare workflow.

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