Review Article *Open Access*

Journal of Progressive Medicine and Health Care

ISSN: 3070-2305

DOI: doi.org/10.63721/26JPMHC118

Influence of Hybrid Intelligence on Expertise Decision-Making

Jane Marie Cioffi

Retired Adjunct Associate Professor, Department of Nursing and Midwifery, Western Sydney University

Citation: *Jane Marie Cioffi (2026) Integrative Influence of hybrid intelligence on expertise decision-making. J. of Pro Med and Hea Care 2(3), 1-8. WMJ/JPMHC-118*

Abstract

With hybrid intelligence the increased use of artificial intelligence can put at risk clinical expertise in decision-making. Clinical expertise is developed through years of deliberate practice, and this process is altered when artificial intelligence support is applied in clinical decision-making as opportunities for learning particularly in complex decision-making situations are reduced. This paper discusses clinical decision-making in relation to hybrid intelligence and clinical expertise and identifies strategies to address acquisition of expertise to accommodate the transition to the use of artificial intelligence in the clinical context. In conclusion the use of hybrid intelligence affects clinical expertise as artificial intelligence has the capacity to fundamentally alter clinical learning and practice. Clinicians must be able to oversee artificial intelligence generated decisions. This requires consideration of educational strategies to ensure clinical expertise in artificial intelligence use is addressed proactively. Research is needed to identify effective strategies for interventions for development and retention of expertise suited to hybrid decision-making environments and to explore and describe the collaboration between the human and artificial intelligence as co-agents.

***Corresponding author**: Jane Marie Cioffi, Retired Adjunct Associate Professor Department of Nursing and Midwifery, Western Sydney University, Australia.

Submitted: 27.04.2026 **Accepted**: 02.05.2026 **Published**: 28.05.2026

Keywords: Artificial Intelligence, Clinical Decision-Making, Expertise, Expertise Development, Hybrid Intelligence

List of Abbreviations

Artificial intelligence (AI)

Introduction

The shift toward hybrid systems focuses on humans and machines being good at fundamentally different things [1]. Artificial intelligence (AI) is not a simple replacement or a basic add-on to human judgment. While humans excel in subjective judgment, contextual understanding, and ethical reasoning, AI systems

augment decision-making by processing vast datasets, identifying patterns, and simulating scenarios with unparalleled speed and precision [2]. In accordance with Dellermann et al [3]. hybrid intelligence is defined as the ability to achieve complex goals by combining human and artificial intelligence, thereby reaching superior results to those each of them could have accomplished separately. Oversight of AI relies on expertise. This paper discusses clinical decision-making in relation to hybrid intelligence and clinical expertise and identifies strategies to address acquisition of expertise to accommodate the transition to the use of artificial intelligence in the clinical context.

Hybrid Intelligence and Clinical Decision-Making

Hybrid decision-making has the underlying core concepts of distributed cognition and cognitive complementarity with distributed cognition theory being considered as an entire interconnected system. Distributed cognition emphasises the distributed nature of cognitive phenomena across individuals, artefacts and internal and external representations in terms of a common language [4]. The traditional view of cognition shifts from being a localised phenomenon of information processing at the level of the individual to cognition being better understood as a distributed phenomenon [5]. It focuses on the processes of an individual; on an individual in coordination with a set of tools; or on a group of individuals in interaction with each other and a set of tools. Collaborative complementarity grows out of interaction and feedback between the human and AI where human and machine strengths amplify each other and drive effectiveness. Both information asymmetry that is humans knowing things about context that the AI simply cannot access and capability asymmetry that is the mutual need created by different cognitive strengths are drivers of this potential.[1] Different levels of available information (information asymmetry) and different capabilities to process this information (capability asymmetry) may generate discrepancies in decision outcomes [6].

Human–AI collaboration has been described as evolving through three progressive configurations of interaction: partial replacement, complementation, and augmentation [7,3]. Each stage reflects a different balance of responsibility and agency between the human and AI systems. In the partial replacement configuration, AI systems are primarily used to automate repetitive, routine, or logistical tasks that do not require nuanced pedagogical judgement [7]. Time and cognitive load are eased by offloading standardised functions to AI. In complementation humans and AI systems perform different but interconnected aspects in a decision-making situation. In this arrangement, AI might generate formative feedback while the human adds interpretive depth, explaining the rationale behind the feedback so adapting it to the specific clinical decision-making situation. AI brings computational efficiency and pattern recognition, while the clinician provides contextual judgement, empathy, and ethical sensitivity. The final stage, augmentation, involves the deliberate amplification of human capabilities through intelligent assistance. This progression, from replacement to complementation to augmentation, illustrates a shift from automation to collaboration, and ultimately towards co-agency, in which human and machine roles are dynamically negotiated [8].

Specifically human - AI decision-making is a human-AI collaboration [9]. The increasing abilities of AI have contributed to the strengths of hybrid intelligence in clinical decision-making as it addresses the essential role of clinical judgment while leveraging AI's networked world of information and computer-mediated interactions emerge as a dynamic of interaction for the clinician [10,17]. The distribution of cognitive work between humans and AI situates AI within clinical decision-making as a distributed cognitive resource rather than an autonomous decision-maker[10]. Hybrid decision-making in clinical practice integrates AI-driven data analysis with clinical expertise enabling clinicians to apply their critical thinking, intuition, and ethical reasoning to decision-making so enhancing clinician performance with the limitations of AI being considered [11]. For example, there are limitations with humanistic and social dimensions of patient care involving understanding of suffering and demoralisation that are not adequately addressed for example with artificial generated risk scores [12].

Significant metacognitive awareness and strategies are required with the use of AI [13] that involve clinical expertise. Clinical expertise is critical as the decisions generated by AI require clinicians to recognise and reject incorrect system advice [14]. This involves clinicians evaluating both their own judgements and those generated by the clinical AI system then integrating both judgements effectively to arrive at a final decision [15]. They must be able to challenge and question for example

decision transparency and explanations underlying reasoning [16,17]. Clinicians must have oversight of AI driven decisions so decisions can be modified in real time and moral responsibility and legal liability for final decisions can be held, specifically regarding incorrect decisions [18,19]. Each clinical decision must be legally defensible [20].

Clinical Decision-Making and Expertise

Dual-process theories of judgment and decision-making describe two cognitive processes System 1, characterized by fast, intuitive, and affective processing, and System 2, defined by slow, deliberative, and analytical reasoning [21]. When making decisions clinicians blend knowledge, intuition and experience and use System 1 and 2 modes of thinking[21,22]. In the cognitive process clinicians analyse (critically think), apply (clinically reason) and act (clinically judge) [23,24]. A hallmark of expertise in clinical decision-making is the use of inner cognitive cues that prompt the use of abstract knowledge representation and the most clinically relevant information [25] that inherently hold clinical gestalt in specific patterns of signs and symptoms intuitively leading to clinical judgements [26]. When clinical decision-making occurs in a hybrid context increasing reliance on external cognitive agents such as algorithms can occur. In this situation the decision maker may no longer construct an answer but may adopt one generated by an external system [27]. To accommodate the hybrid cognitive environment Shaw and Nave propose System 3 as an exterior mode of thinking that accompanies System 1 and 2, interior modes of thinking [27].

An expert is a person who no longer depends on rules, guidelines or maxims; has an intuitive grip of situations established on deep, tacit understanding; has analytical methods used only in new situations; has a vision of what is possible and possesses superior know-how (procedural knowledge, or ability to carry out actions) automatically performing tasks without conscious monitoring [28]. The expertise of a professional has been identified as a multidimensional construct that comprises declarative knowledge (knowing that), procedural knowledge (knowing how), and conditional knowledge (knowing when and where or under what conditions) [29]. Experts' instinctive actions are related to relevant past experiences, pattern recognition and skilled know-how [30].

Expertise is a complex and dynamic construct that can be regarded not only as a sum of attributes a person possesses (e.g., knowledge and skills) but as manifested in superior performance in a specific work domain in the form of consistently demonstrated actions that are both optimally efficient in their execution and effective in their results [31]. With the use of AI support risks of de-skilling from reliance on AI support and erosion of expertise and its acquisition are possible.

Acquisition of Expertise for Clinical Decision-Making

After many years of studying experts in various fields Ericsson concluded expertise develops through years of deliberate practice and coaching [32]. Ericsson explained an important distinguishing feature of deliberate practice is it involves sustained effort to practice tasks in which the individual is not as yet proficient [32]. According to Ardichvili the process of expertise development needs to include a variety of inter-connected activities (e.g., deliberate practice, engaging in progressively more challenging work activities that provide learning opportunities, and learning informally from expert coaches and peers) [33].

Central to the acquisition of clinical expertise is direct engagement in clinical encounters where the opportunity exists for the process of expertise development to occur. According to Benner [34] the development of clinical nursing expertise occurs in practice where a nurse tests and refines both theoretical and practical knowledge in actual clinical situations accompanied by reflection on encountered circumstances that refines moment-to-moment decision-making at an unconscious, intuitive level [35]. A recent concept analysis of clinical nursing expertise confirmed that deliberate accumulation of relevant experience and contextual connections within immersion in clinical practice are essential elements [30]. In medicine according to Patel et al. [36], expert performance requires about 10 years of devoted effort by clinicians to accumulate knowledge bases of large stores of information with comprehensiveness and organization. The acquisition of clinical expertise is therefore dependent on immersion in clinical practice with encounters in increasing complexity.

The Impact of AI on Clinical Expertise

In AI clinical experts act as "human-in-the-loop" decision-makers who interpret AI insights, manage complex, unpredictable scenarios, and ensure that

digital tools enhance rather than replace the human connection in healthcare [37]. Automation enables large volumes of data to be processed quickly, complex patterns in data to be detected better and if the patterns are relatively stable and predictable over time performance can be improved through learning from previous errors to reduce for example susceptibility to cognitive biases [33]. AI brings data-driven insights, computational power, and process automation capabilities and the expertise of the clinician acts to complement by contributing to the decision-making process [38,2]. However, in the hybrid environment technology is not able to address contextual judgment, ethical oversight, and personalized patient care that clinical expertise provides [39].

In this changed clinical context of practice AI results in reducing deliberate practice or experimentation [40,41]. The opportunity to learn and develop clinical expertise diminishes and novices and less experienced clinicians are no longer able to engage in processes that develop expertise to the same extent. Consequences with AI use are cognitive offloading that reduces memory tasks and reasoning steps that decreases cognitive effort, increased risk to calibration in the judgement processes from over trust in system outputs and failure to determine error impaired learning as causal reasoning and decision outcome links are obscure and the outsourcing of a decision to an external tool (cognitive surrender) that involves a deeper abdication of critical evaluation, where the user relinquishes cognitive control and adopts the AI's judgment as their own [42-45,27]. Further in complex clinical decision-making situations readiness with non-routine tasks and procedural skills are reduced leading to stagnation and regression [44]. These consequences threaten the process of expertise development. Overall opportunities for developing expertise are eroded including the processes of redistribution of cognitive tasks and mediation of access to knowledge and learning opportunities. Expertise is challenged with the use of AI.

A series of studies confirmed the negative effects of knowledge support systems and AI [40,4]. For example, decision makers who trust AI more and engage in less effortful analytic thinking (lower cognitive reflection and fluid intelligence) are more likely to display cognitive surrender and the implementation of AI technologies has been shown to result in the loss of opportunities to acquire skills through on-the-job learning [46,27]. The use of technology reduces the performing of important cognitive tasks resulting in a narrower, less comprehensive understanding of the whole process of clinical decision-making [46].

With AI use expertise development is impaired as opportunities for learning from repeated performance of progressively more complex tasks; diminished ability to engage in deliberate learning by practicing difficult and not-yet-mastered tasks; and informal and incidental learning are reduced [29]. A significant risk to adaptive expertise (the capacity to apply existing knowledge and skills to novel, complex, or unexpected situations) arises with AI as it encourages surface learning, reduces problem-solving skills, fails to develop the habits and mindsets necessary for lifelong learning and professional identity formation that leads to AI induced deskilling [47]. Less experienced clinicians and novices learning and consolidation of knowledge and skills are particularly vulnerable to AI-induced deskilling [48]. When the learning opportunities that develop adaptive expertise are systematically reduced, judgment, flexibility, and retention of mechanistic understanding weaken so producing clinicians who excel only in tightly defined, well-supported situations but struggle when faced with ambiguity or novel challenges [49]. More concerning is never-skilling (the failure to develop essential skills in the first place) that can occur in clinical contexts where there is continuous over-reliance on AI and decision-support tools for learning and clinical reasoning, without reflection or critical appraisal of their output. When clinicians repeatedly offload cognitive tasks cognitive processing becomes more automatic. This transformation makes individuals efficient in familiar, well-supported situations but less adaptable and resilient when facing novel or complex challenges [50]. Over time, this displacement produces clinicians who excel at matching presentations to known frameworks but struggle when patients deviate from textbook patterns [48]. Dependence on automation can generate clinicians less likely to understand the information presented by machine output so lessening the clinical value able to be provided. If all the clinician is familiar with is an algorithmic approach, they are unlikely to have skills in error recognition and recovery to rescue due to lack of skills in procedural practice and incapability to carry out the meta cognition necessary to perform complex clinical decisions [51]. Consequently, the pool of clinicians capable of developing their

expertise and, with time, reaching higher levels of expertise shrinks with novices and less experienced clinicians having progressively smaller numbers of opportunities to develop expertise through repeated performance.

Strategies to Address Clinical Expertise in an Automation Context

As the use of hybrid intelligence has the potential to affect clinical expertise a proactive approach to protect expertise and to make sure that adoption of AI technologies enhances rather than replace expertise is needed [50]. The capacity of AI to fundamentally alter clinical learning and practice has been shown to result in clinicians who are highly efficient but less capable of independent problem-solving and critical evaluation compared to pre-AI counterparts [52]. Deep tacit knowledge erosion, over-reliance on AI recommendations and reduced development of clinical intuition can potentially result and cognitive off-loading and surrender of complex tasks such as clinical reasoning can lead to "deskilling," "never-skilling," or "mis-skilling" [52,27]. By targeting alternative development opportunities with augmentation strategies, the potential impact of automation on expertise development can combat expertise loss and progress expertise development.

Practice without automation that brings exposure to clinical complexity is critical for the preparation of entry-level professionals in academic institutions. Case studies and /or simulations can provide novices with clinical situations in which they can analyse complex data, problem solve and develop analogical reasoning [53]. Repeated clinical participation in progressively more complex problem solving and practice sessions that are totally free from digital aids allow certain amounts of inefficiency and risk to be encountered bringing challenge and complexity that are integral parts of the learning process [54]. Regular practice on unsupported reasoning and active problem-solving exercises can develop clinical reasoning skills [38]. Strategies like these enable the reality of practice to be encountered.

AI literacy for clinicians should include technical understanding, critical appraisal, and practical application as clinicians need to be able to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online in the workplace [55,56]. Furthermore, Ng et al., confirm this stating that instead of merely knowing how to use AI applications, the underlying AI concepts and ethical concerns of AI applications are needed that Pupic et al, consider should include AI ethics and interpretability [57,58]. Practicing clinicians need AI literacy to understand algorithmic bias, limitations of AI and conditions of uncertainty with a broad range of foundational knowledge to understand the intricacies of data and fundamental concepts like risk prediction or causality [59]. Importantly novices and less experienced clinicians need to be encouraged to be self-directed, so they further develop their expertise even in the face of automation-induced barriers to learning.

Competency is essential to use AI technologies effectively [48]. Three tiers of clinical AI expertise are proposed: basic, proficient and expert skills [58]. Strategies need to be employed to build and strengthen skills in the use of AI such as reflective exercises that encourage explanations of the reasoning processes being used and critical reflection on how external aids influence thinking both with and without AI so developing critical evaluation and verification of AI outputs [48]. In addition, teaching explicitly about the cognitive risks of overreliance on technological supports is also of utmost importance to foster awareness of when and how to use AI technologies productively.

As human-AI collaboration redefines expertise with clinical expertise shifting from individual and tacit to distributed and system mediated a conceptual framework for human-AI collaboration in decision-making needs to be developed [45]. The synergy between human-AI skills to arrive at competencies that ensures necessary capacities for an automated clinical context needs to be articulated [48]. Therefore identifying the expertise clinicians will need with automated agents in an automated context is critical. Expertise for automation where cognitive work is distributed between the clinician and the system must address how to bring knowing how to work with systems that assist in clinical decision-making. This will require system navigation capability, balancing tacit knowledge development with digital literacy, avoiding over reliance on AI and maintaining critical judgement as a part of this configuration. The attributes of the evolving co-agency role need to be described.

Research studies designed to explore and identify the

acquisition of expertise in a hybrid environment are recommended. The evidence currently is fragmented, and the field lacks a coherent research agenda [47]. A focus on the development of clinical expertise to achieve and retain expert performance as well as the consideration of the collaboration between the human and AI, and its determination of the type of expertise is needed to identify effective strategies for interventions for expertise development suited to hybrid decision-making environments. Another fundamental question open to further study involves what happens when core building blocks of clinical thought, such as inference, evaluation, and justification, are outsourced to artificial systems. This focuses on a process-oriented view: understanding how clinicians engage artificial cognition (e.g., knowledge navigation and management), which cognitive paths they follow (e.g., surrender, offloading), who is most susceptible or resistant, and what conditions modulate these patterns [27].

Conclusion

In conclusion hybrid intelligence applications in clinical decision-making impact clinicians affecting clinical expertise as AI has the capacity to fundamentally alter clinical learning and practice. Clinicians must be able to oversee AI generated decisions. This requires consideration of educational strategies to ensure clinical expertise is addressed proactively. Research into the type of expertise needed for co-agency with AI and effective educational strategies to address deskilling is recommended.

References

1. Dimitrov N (2025) Hybrid strategic decision making: The synergy between expert judgement and AI system recommendations. JOMA 4: 147-163.
2. Venigandla, K, Vemuri N, Vemuri N (2024) Hybrid intelligence systems combining human expertise and AI/RPA for complex problem solving. Int J Innov Sci Res Technol 2066-2075.
3. Dellerman D, Ebel P, Söllner M, Leimeister J (2019) Hybrid Intelligence. Bus Inform Syst Eng 61: 637-643.
4. Malone T, Bernstein M (2015) Handbook of collective intelligence. Cambridge, MIT Press https://mitpress.mit.edu/9780262545846/handbook-of-collective-intelligence/ .
5. Hutchins E (2006) The distributed cognition. Perspective on human interaction. In Enfield. J. Levinson S. (Eds) Roots of Human Sociality: Culture, Cognition and Interaction 375-398.
6. Hemmer P, Schemmer M, Kühl N, Vössing M, Satzger G (2025) Complementarity in human-AI collaboration: concept, sources, and evidence, Eur J Inf Syst 34: 979-1002.
7. Akata Z, Balliet D, M DeRijke M, F Dignum F, V Dignum V, et al (2020) A research agenda for hybrid intelligence: Augmenting human intellect with collaborative, adaptive, responsible, and explainable artificial intelligence. Comput 53: 18-28.
8. Oyelere, S (2026) A Scoping Review of Hybrid Intelligence Systems for Human-Centred AI in Education. Comput Hum Behav Artif Hum 7: 100-273.
9. Lai V, Chen C, Smith-Renner A, Liao Q, Tan C (2023) Towards a science of human-AI decision making: An overview of design space in empirical human-subject studies. Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency, Chicago, USA 1369-1385.
10. Hollan J, Hutchins E, Kirsh D (2000) Distributed cognition: Toward a new foundation for human-computer interaction research. ACM Trans Comput-Hum Interact 7: 174-196.
11. Mennella C, Maniscalco U, De Pietro G, Esposito M (2024) Ethical and regulatory challenges of AI technologies in healthcare: a narrative review. Heliyon 10: e26297.
12. Clarke, D, Kissane D (2002) Demoralization: its phenomenology and importance. Aust N Z J Psychiatry 36: 733-742.
13. Tankelevitch L, Kewenig V, Simkute A, Scott A, Sarkar A, et al (2024) The Metacognitive Demands and Opportunities of Generative AI. Proceedings of the CHI Conference on Human Factors in Computing Systems 1-24.
14. Schemmer M, Bartos A, Spitzer P, Hemmer P, Liebschner J, et al (2023) Towards effective human-AI decision-making: The role of human learning in appropriate reliance on AI advice. 44th International Conference on Information Systems; Oct 3; Hyderabad, India https://arxiv.org/abs/2310.02108 .
15. Jussupow E, Spohrer K, Heinzl A, Gawlitza J (2021). Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. ISR. 32 :713-

735.
16. Racine E, Boehlen W, Sample M (2019) Healthcare uses of artificial intelligence: Challenges and opportunities for growth. Healthc Manage Forum 32: 272-275.
17. Floridi L, Cowls J, Beltrametti M, Chatila R, Chazerand P, et al (2018) AI4People -An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Min Mach 28: 689-707.
18. Smith H, Birchley G, Ives J (2023) Artificial intelligence in clinical decision-making: Rethinking personal moral responsibility. Bioeth 38: 78-86.
19. Khairat S, Marc D, Crosby W, Al Sanousi A (2018) Reasons for physicians not adopting clinical decision support systems: critical analysis. MIR Medical Informatics 6 e24. https://doi: 10.2196/medinform.8912.
20. McCradden M, Stedman I (2024) Explaining decisions without explainability? Artificial intelligence and medicolegal accountability. Future Hosp J. 11: 100171.
21. Kahneman D (2011) Thinking, fast and slow. New York: Farrar, Straus and Giroux https://psycnet.apa.org/record/2011-26535-000 .
22. Bragazzi N, Garbarino S (2024) Towards clinical generative AI: Conceptual framework. JMIR AI. 3:e 55957 https://doi: 10.2196/55957.
23. Victor-Chmil J (2013) Critical thinking versus clinical reasoning versus clinical judgment: Differential diagnosis. Nurse Educ 38: 34– 36.
24. Lee D, Park J (2019) A Review for Concept Clarification of Critical Thinking, Clinical Reasoning, and Clinical Judgment in Nursing Education. J Korean Acad Soc Nurs Educ 25: 378-387.
25. Tikhomirov L, Semmler C, McCradden M, Searston R, Ghassemi M, et al (2024) Medical artificial intelligence for clinicians: the lost cognitive perspective Lancet digit Health 6: e589-e594.
26. Dale J, Hallas D, Spratling R (2019) Critiquing Research Evidence for Use in Practice: Revisited. J Pediatr Health Care 33: 342-346.
27. Shaw S, Nave G (2026) Thinking—Fast, Slow, and Artificial: How AI is Reshaping Human Reasoning and the Rise of Cognitive Surrender. https://osf.io/preprints/psyarxiv/yk25n_v1 .
28. Dreyfus H, Dreyfus S (1986) Mind over machine: The power of human intuition and expertise in the era of the computer. Basil Blackweli, Oxford: https://dl.acm.org/doi/abs/10.5555/7916 .
29. Evers A, van der Heijden B (2017) Competence and professional expertise. In M. Mulder (Ed), Competence-based vocational and professional education 23: 83-101.
30. Hecht J, Heitkemper E, Danesh V, Clark A, Yoder L (2026) A concept analysis of expertise associated with practicing clinical nurses in hospital settings. J Adv Nurs 1:1-12.
31. Herling R (2000) Operational definitions of expertise and competence. Adv. Dev. Hum Resour 2: 8-21.
32. Ericsson, K (2009) Development of professional expertise: Toward measurement of expert performance and design of optimal learning environments. Cambridge University Press.
33. Ardichvili A, (2022) The impact of artificial intelligence on expertise development: Implications for HRD Adv. Dev. Hum Resour 24: 78–98.
34. Benner, P. (1984) From novice to expert. Am J Nsg 82: 402–407.
35. Simmons, B, Lanuza D, Fonteyn M, Hicks F, Holm K (2003) Clinical Reasoning in Experienced Nurses. West J Nurs Res 25: 701- 719.
36. Patel V, Glaser R, Arocha J (2000) Cognition and expertise: Acquisition of medical competence. Clin Invest Med 23: 256-60.
37. Horvitz E (1999) Principles of mixed-initiative user interfaces. In CHI '99: Proceedings of the SIGCHI conference on Human Factors in Computing Systems: 159 – 166. https://doi.org/10.1145/302979.303030.
38. Sokol K, Fackler J, Vogt J (2025) Artificial intelligence should genuinely support clinical reasoning and decision making to bridge the translational gap. npj Digit. Med 8: 345. https://doi.org/10.1038/s41746-025-01725-9.
39. Iyad Rahwan, Manuel Cebrian, Nick Obradovich, Josh Bongard, Jean-François Bonnefon, et al (2019) Machine behavior. Nature 568: 477- 486.
40. Vicky Arnold, Philip A Collier, Stewart A Leech, Steve G Sutton (2004) Impact of intelligent decision aids on expert and novice decision-makers' judgments. Acc Fin 44: 1-26.
41. Arnold V, Clark N, Collier P, Leech S, Sutton S (2006) The differential use and effect of knowledge-based system explanations in novice and expert judgment decisions 30: 79–97.

42. Evan F Risko, Sam J Gilbert (2016) Cognitive offloading. Trends Cogn Sci 20: 678-688.
43. Parasuraman R, Riley V (1997) Humans and automation: Use, misuse, disuse, abuse. Hum Factors 39: 230–253.
44. Cabitza F, Rasoini R, Gensini G (2017) Unintended consequences of machine learning in medicine. JAMA 318: 517–518.
45. Topol E (2019) Deep medicine: How artificial intelligence can make healthcare human again. Basic Books.
46. Beane M (2019) Learning to work with intelligent machines. Harv. Bus. Rev Sept- Oct: 140–148.
47. Natali C, Marconi L, Dias Duran L, Miglioretti M, Cabitza F (2025) AI-induced deskilling in medicine: a mixed-method review and research agenda for healthcare and beyond. Artif Intell Rev 58: 356
48. Tarhouny S, Farghaly A (2026) Deskilling dilemma: brain over automation. Front Med 13: 1765692
49. Drabiak K, Kyzer S, Nemov V, El Naqa I (2023) AI and machine learning ethics, law, diversity, and global impact. Br J Radiol 96: 20220934
50. Sunday O (2025) Behavioral impacts of AI reliance in diagnostics: balancing automation with skill retention. Epidemiol Health Data Insights 1: ehdi011
51. Verghese A, Charlton B, Kassirer JP, Ramsey M, Ioannidis JP (2015) Inadequacies of physical examination as a cause of medical errors and adverse events: A collection of vignettes. Am J Med 128:1322-1324.
52. Ritter A (2026) Educational strategies for clinical supervision of AI Use. The Hospitalist https://www.the-hospitalist.org/hospitalist/article/40662/in-the-literature/educational-strategies-for-clinical-supervision-of-ai-use/
53. Arnold V, Collier P A, Leech S A, Sutton S G, Vincent A (2013) INCASE: Simulating experience to accelerate expertise development by knowledge workers. Intell. Syst. Account. Finance Manag 1: 1-21.
54. Edwards H (2025) Preserving Human Expertise in the Age of AI. Artificiality Institute https://doi:artificialityinstitute.org/preservinghuman-expertise-in-the-age-of-ai/.
55. Laupichler M, Aster A, Haverkamp N, Raupach T (2023) Development of the "Scale for the assessment of non-experts' AI literacy" – an exploratory factor analysis. Comput Hum Behav Rep 12.
56. Long D, Magerko B (2020) What is AI literacy? Competencies and design considerations. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems 1: 16.
57. Ng D, Leung J, Chu K, Qiao M (2021) AI literacy: Definition, teaching, evaluation and ethical issues Proceedings of the Association for Information Science and Technology 58: 504-509.
58. Pupic N, Ghaffarizadeh S, Hu R, Singla R, Darras K, et al (2023) An evidence-based approach to artificial intelligence education for medical students: A systematic review. PLOS Dig Health 2:e0000255 https://pubmed.ncbi.nlm.nih.gov/38011214/ .
59. Schubert T, Oosterlinck T, Stevens R, Maxwell P, van der Schaar M (2024) AI education for clinicians. EClinical Medicine 79: 10296.