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Expertise Erosion, Skill Dependency, and Tacit Knowledge Loss Inside Automated Workflows

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Abstract

Automation promises faster and more scalable work, yet its consequences for human expertise remain unsettled. Systems that improve assisted performance can also reduce task participation, alter legitimate knowledge, intensify reliance, and narrow everyday learning opportunities. This Critical Review Article examines that expertise paradox by integrating evidence on tacit knowledge, skill dependency and deskilling, informal workplace learning, and conditions that may preserve expertise inside automated workflows. The review combines structured evidence identification and screening with critical synthesis of mechanisms, contradictions, alternative explanations, and boundary conditions. The literature does not support a simple conclusion that automation either erodes or augments expertise. Instead, it indicates heterogeneous trajectories shaped by task exposure, epistemic visibility, work design, career stage, opportunities for practice and feedback, human–AI calibration, and the organization of knowledge exchange. The article proposes an Expertise-Resilience Framework that distinguishes erosion pathways from resilience pathways while treating their connections as original integrative synthesis rather than a validated causal model. It also identifies unresolved problems involving unaided competence, knowledge transfer, occupational hierarchy, failure recovery, and multilevel inference. Its contribution is a bounded organizational account of when automated workflows may weaken, redistribute, or help sustain expertise and what evidence would be required to discriminate among these possibilities.

Keywords: Expertise erosion, Skill dependency, The expertise paradox of automation, Tacit knowledge loss, Conditions that preserve expertise, Expertise-resilience framework

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Introduction

Automation is often evaluated through a substitution question: which human activities can be transferred to a technical system without sacrificing output? That framing is incomplete because automation and augmentation can operate simultaneously and can become mutually dependent organizational logics [1]. An automated workflow may increase speed or consistency while also changing who observes the task, who interprets exceptions, who diagnoses failures, and who retains opportunities to exercise judgment. Algorithmic systems likewise reorganize direction, evaluation, visibility, and discretion, creating contested forms of control rather than functioning as neutral substitutes for labor [2]. The organizational problem is therefore how redistributed work changes the conditions under which expertise is used, maintained, transferred, and renewed.

Expertise is not equivalent to occupational status, accumulated tenure, or formal responsibility. It involves domain-specific knowledge and judgment developed through repeated engagement, updating, discrimination among situations, and experience with consequential variation [3]. Automated workflows can alter this developmental infrastructure when workers no longer participate in tasks that previously supplied practice, feedback, error exposure, or observation of experienced colleagues. In robotic surgery, approved training arrangements could restrict novices' hands-on participation and stimulate unofficial "shadow learning" practices intended to recover access to practical skill formation [4]. This does not establish inevitable degradation. It shows why performance indicators may overlook a slower consequence: activities removed by automation may also have supported future competence and situated judgment.

The problem extends from skill practice to organizational knowing. AI development can privilege explicit expert labels while failing to capture uncertainty and situated know-how embedded in professional practice [5]. An organization can therefore preserve an observable decision output while losing access to parts of the reasoning, interpretation, and contextual discrimination that previously produced it. At the performance level, a multicentre observational study reported lower unaided adenoma-detection performance after sustained AI exposure, a pattern consistent with deskilling risk but insufficient to establish that AI exposure caused the decline [6]. These findings motivate a critical review rather than an erosion thesis. The objective is to evaluate when automated workflows attenuate, redistribute, or preserve expertise by connecting tacit knowledge loss, skill dependency, informal learning, and preservation conditions. The contribution lies in explaining their relationships while distinguishing descriptive evidence from causal inference, assisted performance from retained capability, and an integrative conceptual framework from empirical validation.

Critical review method

The review was designed as a critical review rather than a systematic effectiveness review. Its questions concerned how automated workflows affect tacit knowing, dependence on automated performance, opportunities for informal learning, and conditions under which human expertise may remain resilient. Review design, search logic, selection, extraction, and synthesis were specified transparently because review rigor depends on aligning the method with the intended scholarly contribution [7]. Information sources included target-journal and publisher searches, DOI-indexed construct and mechanism searches, and backward or forward citation chaining. Search concepts combined automation, expertise erosion, deskilling, tacit knowledge, informal learning, work design, delegation, algorithmic literacy, and human–AI collaboration. Eligible articles had to be peer reviewed, directly relevant, and sufficiently documented to identify design, context, mechanism or association, limitation, and interpretation boundary.

Critical review requires interrogation of assumptions, contradictions, omissions, and conceptual boundaries rather than accumulation of superficially similar findings [8]. PRISMA-compatible reporting was used only to make evidence identification and selection auditable [9]. Reporting distinguished record appearances, unique records, retrieval failures, full-text assessment, and reason-specific exclusions [10]. The searches produced 58 record appearances: 29 from target-journal, publisher, and DOI searches, 21 from construct or mechanism searches, and 8 from citation chaining. Six duplicate appearances were removed, leaving 52 unique records for screening. Eight were excluded at title and abstract; 44 reports were sought, 2 were unavailable, and 42 full texts were assessed. Six full texts were excluded for verified fit, redundancy, overlap, or scope reasons, leaving 36 sources for critical synthesis. These procedures increase transparency without establishing exhaustive coverage or changing the review design.

Figure 1 reports the verified flow of records through identification, duplicate removal, screening, full-text assessment, exclusion, and final inclusion for this critical review article.

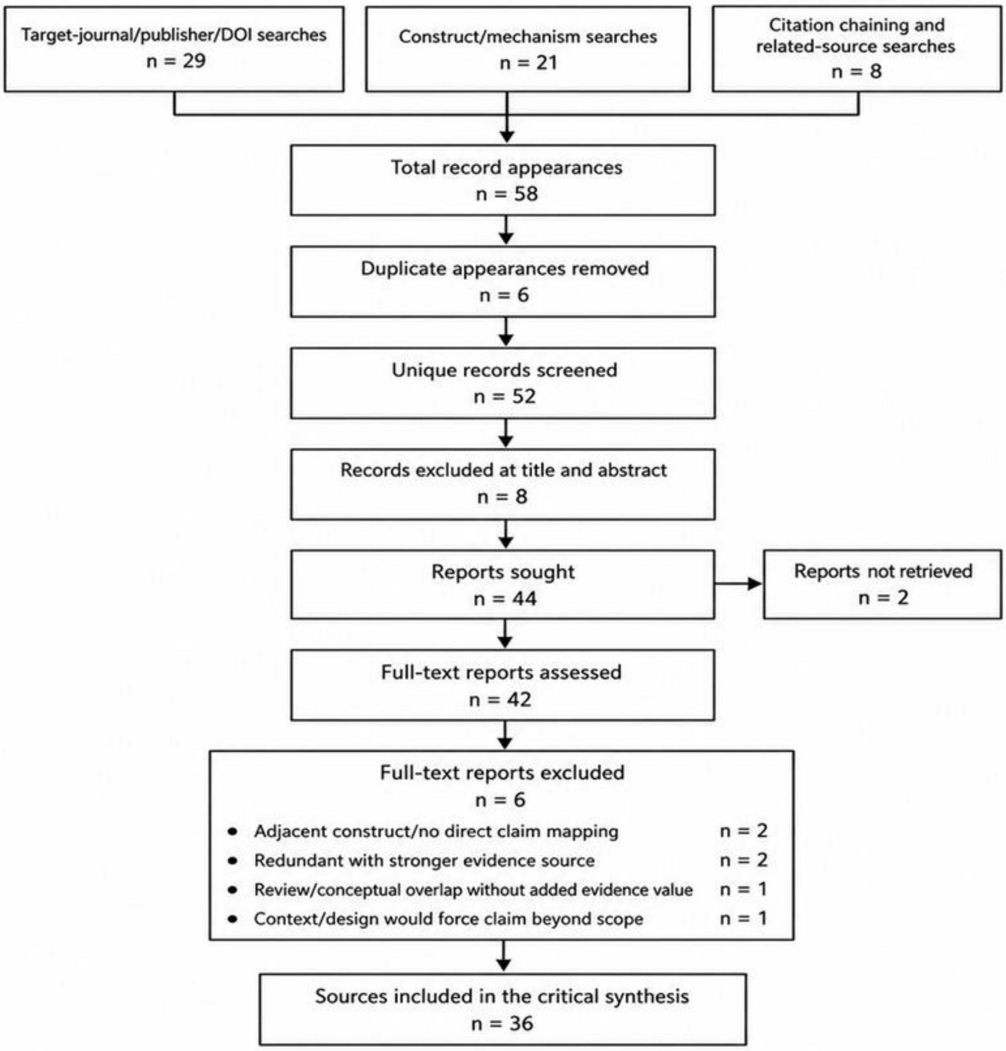

Figure 1. PRISMA Flow Diagram for Evidence Identification and Selection

Tacit knowledge loss

Tacit knowledge loss is best treated here as attenuation, inaccessibility, or displacement of situated know-how rather than disappearance of all expert knowledge. Learning algorithms can reorganize what becomes codified, delegated, visible, and contestable; implementation can alter a workplace's regime of knowing; and black-boxing practices can make analytical processes less inspectable while reorganizing expert work [11-13]. These studies converge on epistemic reconfiguration, but they do not demonstrate a common magnitude of knowledge loss or prove that reduced visibility equals reduced competence. The critical distinction is among what workers know, what they are permitted or required to enact, and what an automated workflow makes observable and consequential. Automation may therefore weaken conditions for expertise maintenance even before knowledge demonstrably disappears, because situated reasoning can become less frequently exercised, less visible to others, or less influential in organizational decisions.

Evidence also conflicts with a simple erosion account. In a long ethnographic study of learning algorithms in policing, knowledge brokers became important because algorithmic outputs still required interpretation, curation, and connection to occupational knowledge [14]. Automation can therefore redistribute expertise and create new brokerage dependencies rather than simply eliminating human knowing. Such redistribution may preserve situated interpretation while concentrating it in particular roles, producing a different vulnerability: an organization may remain capable because a small set of actors connects technical outputs with contextual practice. Whether this arrangement represents resilience depends on the accessibility, transferability, and continuity of that brokerage capacity. The evidence is consequently compatible with attenuation and reconfiguration, depending on whether practical knowledge remains available, socially distributed, and consequential when automated recommendations encounter ambiguity or exceptions.

A further counterpoint comes from AI development for hiring. Attempts to reduce expert involvement encountered limits to codification and evolved toward hybrid arrangements in which developers and domain experts learned from one another [15]. Tacit knowledge can thus resist straightforward substitution and may become more visible precisely when efforts to formalize expertise expose what cannot readily be represented as rules or labels. Yet this development context does not establish that deployed systems routinely generate mutual learning, nor that recognizing codification limits ensures preservation of occupational expertise. A critical account must therefore distinguish knowledge made newly explicit, knowledge redistributed among roles, and knowledge that becomes progressively inaccessible through reduced enactment.

Table 1 clarifies how the critical review separates forms of expertise change, the organizational processes through which they may arise, and the boundaries required when interpreting evidence from automated workflows.

Table 1. Critical-review architecture for interpreting expertise change inside automated workflows

Analytical domain	What the review examines	Key distinction to preserve	Organizational process of interest	Critical synthesis function	Interpretation boundary
Expertise continuity	Whether workers retain usable domain knowledge and judgment after workflow automation	Current task performance vs retained capability	Continued practice, feedback, exception exposure	Defines what counts as expertise preservation	High assisted performance does not demonstrate durable expertise
Tacit knowledge	Whether situated know-how remains accessible, enacted, and transferable	Knowledge loss vs knowledge redistribution	Articulation, observation, brokerage, contextual interpretation	Identifies epistemic changes hidden by output metrics	Reduced visibility does not necessarily mean knowledge has disappeared
Skill dependency	Whether competent performance increasingly presupposes automated assistance	Technology use vs dependence	Reliance, delegation, monitoring, manual task withdrawal	Separates ordinary tool use from vulnerability to system absence	Dependence must not be inferred from adoption alone
Deskilling	Whether unaided human capability weakens over time	Changing job requirements vs declining competence	Reduced rehearsal, complacency, diminished error diagnosis	Provides the strongest erosion criterion	Deskilling requires longitudinal or otherwise defensible capability evidence
Informal learning	Whether workers continue learning through everyday participation	Formal training vs learning embedded in work	Observation, experimentation, interaction, problem solving	Connects workflow configuration to future expertise formation	Fewer traditional learning occasions may coexist with new digital ones
Expertise resilience	Whether the work system continues reproducing competent judgment and knowledge transfer	Individual competence vs system-level resilience	Task exposure, calibration, reciprocal learning, work design	Integrates preservation mechanisms across levels	Resilience is proposed as conditional, not a validated organizational state

Note. This table is an original critical-review synthesis. It organizes the manuscript's interpretive categories and does not provide effect sizes, evidence rankings, causal thresholds, or validated classifications.

Skill dependency and deskilling

Skill dependency should be distinguished from both technology use and demonstrated deskilling. Dependency describes a work arrangement in which competent performance increasingly presupposes access to an automated system; deskilling requires evidence that human capability itself has weakened or that opportunities necessary for maintaining it have been reduced. A longitudinal organizational case of cognitive automation identifies a plausible process connecting the two: increasing reliance fostered complacency and reduced mindful task engagement, weakening activity awareness, competence maintenance, and the capacity to assess automated output [16]. This process is especially important because deterioration may remain concealed while automation performs reliably; capability deficits become consequential when systems fail, are unavailable, or produce outputs requiring informed challenge. Because the mechanism was developed from a particular organizational case, however, it should be treated as a grounded process explanation requiring further testing rather than a general law of automation.

Workforce evidence further complicates a linear erosion thesis. In Denmark, AI use was associated with heterogeneous changes in within-job skill requirements, with different implications across occupational and skill contexts [17]. Changing requirements can reflect task redesign, substitution, complementarity, or the emergence of new demands; they do not by themselves show that individual workers have lost previously held competence. An organization can become more technologically dependent while some employees develop additional skills, just as individual practical competence can weaken even while formal job descriptions become more sophisticated. Deskilling therefore cannot be inferred from adoption intensity, occupational labels, or changing skill requirements alone. More diagnostic indicators include retained unaided capability, continued exposure to meaningful task variation, ability to detect errors, competence in exceptions, and opportunities to rehearse judgment independently of automated assistance.

Short-run performance evidence provides an important competing explanation. In a randomized field experiment with knowledge workers, generative AI improved speed and quality for tasks inside its capability frontier but reduced correctness on a task outside that frontier [18]. A large workplace rollout likewise found disproportionately larger gains among novice and lower-skill customer-support agents, a pattern consistent with AI making higher-performer practices more accessible [19]. These results demonstrate why augmentation and dependency cannot be treated as opposites. Assisted output may improve while the trajectory of independent capability remains unresolved, and AI may support learning for some workers while reducing practice opportunities for others. Immediate productivity gains therefore do not establish expertise resilience, just as reliance does not automatically prove lasting deskilling. The critical empirical question is whether workers retain the capacity to perform, evaluate, recover, transfer knowledge, and continue learning when automated assistance is unavailable, incorrect, or no longer aligned with the demands of the task.

Informal learning collapse

Informal learning collapse refers here to a substantial narrowing of everyday opportunities through which employees observe, experiment, ask questions, exchange interpretations, and learn by participating in work. It does not imply that all informal learning disappears. Digital ethnography shows that informal workplace learning is woven into routine information seeking, interaction, experimentation, and technology-mediated practice [20]. Automated workflows may therefore affect learning even when formal training remains unchanged. When systems perform intermediate steps, filter information, recommend actions, or remove employees from recurrent task sequences, they can alter the encounters through which workers previously noticed anomalies, compared approaches, and developed practical judgment. Conversely, digital environments can also create new learning opportunities. The relevant question is whether workflow design preserves sufficiently rich participation for workers to develop knowledge rather than merely consume automated outputs.

Learning also depends on collective interpretation. Research on discursive sensemaking around AI indicates that the ways employees understand and discuss machines can shape collaborative workplace learning [21]. Different occupational groups may interpret the same automated system as a tool, authority, constraint, or uncertain partner. Misaligned understandings can reduce the value of interaction even when information is technically accessible. Informal learning collapse should consequently be distinguished from reduced communication volume: abundant interaction may still transmit little expertise if employees lack shared language, access to underlying reasoning, or opportunities to test competing interpretations against task outcomes. The team-level implication remains conditional because qualitative evidence cannot establish that particular forms of sensemaking invariably preserve learning.

Broader workplace evidence reinforces why such opportunities matter. Informal learning behaviors are associated with knowledge and skill acquisition and with performance-related outcomes across heterogeneous work contexts [22]. Yet digital technology simultaneously creates learning opportunities and burdens, including interruption, complexity, and persistent demands to adapt; sustainable learning depends on practices that manage these tensions [23]. Automation can therefore produce both informational abundance and experiential scarcity. A worker may receive more recommendations while encountering fewer occasions to diagnose, deliberate, or explain. The evidence supports treating informal-learning bandwidth as a potential mechanism connecting workflow automation to future expertise, but it does not establish a universal automation-induced learning collapse.

Table 2 reframes the reviewed literature as a set of competing expertise trajectories, highlighting why apparently similar automated workflows may support erosion, redistribution, or resilience under different organizational conditions.

Table 2. Competing expertise trajectories within automated work systems

Analytical tension	Erosion or dependency pathway	Resilience or augmentation pathway	What determines divergence	Central uncertainty	Critical-review interpretation
Automation vs expertise	Human participation contracts as more task components are delegated	Automation frees capacity while preserving consequential human judgment	Which activities remain available for meaningful practice	Whether displaced activity was routine burden or developmental experience	Automation should be evaluated by learning architecture, not task removal alone
Codification vs tacit knowing	Explicit representations displace situated interpretation	Codification reveals where contextual expertise remains indispensable	Degree of task ambiguity and accessibility of expert reasoning	Whether tacit knowledge is lost, concentrated, or translated	Apparent standardization may conceal continued reliance on situated expertise
Reliance vs calibrated delegation	Workers defer to automated outputs and lose diagnostic engagement	Workers selectively delegate while retaining capacity to challenge the system	Feedback quality, error exposure, metaknowledge	Whether calibration persists after prolonged reliable automation	Reliance becomes problematic when independent evaluation capacity deteriorates

Performance vs capability	Assisted output rises while unaided capability becomes uncertain	Assistance accelerates learning and access to effective practices	Career stage, task type, system capability, continued practice	Whether short-run gains transfer to independent performance	Productivity and expertise must be measured separately
Efficiency vs informal learning	Streamlined workflows remove observation, experimentation, and peer exchange	Digital work creates new channels for inquiry and collaborative learning	Social design, task visibility, interaction opportunities	Whether new channels replace the developmental value of removed experiences	Learning loss cannot be inferred from efficiency gains or reduced interaction alone
Senior expertise vs future expertise	Existing experts remain capable while junior developmental access narrows	Knowledge circulates across generations and technical roles	Hierarchy, mentoring structure, reciprocity, access to consequential tasks	Who bears the long-run cost of current efficiency	Organization-level resilience requires reproduction of expertise, not merely retention of incumbents
Technical capability vs organizational resilience	Better systems encourage deeper delegation and latent vulnerability	Better systems complement workers who remain capable of independent judgment	Governance, task allocation, work design, learning safeguards	How long resilience persists as systems improve	Higher technical performance does not automatically strengthen the human knowledge system

Note. This table is an original cross-domain synthesis. "Erosion," "dependency," "resilience," and "augmentation" denote competing interpretive trajectories rather than measured categories, causal effects, or ranked organizational outcomes.

Conditions that preserve expertise

Evidence on expertise preservation suggests that resilience is partly a property of work design rather than an individual employee trait. Digital technologies alter autonomy, task variety, feedback, social interaction, and opportunities for learning depending on how work is organized [24]. Preserving expertise therefore requires more than keeping a nominal human "in the loop." Workers need substantive exposure to task variation, opportunities to make and examine judgments, informative feedback, and sufficient responsibility to maintain diagnostic engagement. These conditions are theoretically plausible and supported by broader work-design evidence, but they have not been validated as a universal intervention package for preventing automation-related skill erosion.

Algorithmic management adds further contingencies because algorithms can themselves function as work designers. Their consequences vary with characteristics such as transparency, fairness, and human influence over task execution [25]. Recent workforce evidence also indicates that algorithmic literacy can complement domain expertise rather than simply replace it, especially when such skills are broadly distributed among domain experts [26]. This complementarity suggests that expertise resilience may depend on employees understanding both the substantive domain and enough of the automated system's operation to evaluate outputs, recognize limits, and communicate effectively with technical specialists. Algorithmic literacy, however, should not be mistaken for domain expertise or treated as a sufficient safeguard against deterioration of practical skill.

Preservation can also be unevenly distributed. Comparative research on inverted apprenticeship shows that senior occupational members may learn new technologies through relationships with juniors while preserving their own status and practical capability, yet some pathways simultaneously restrict junior learning [27]. An organization could therefore appear to retain expertise while shifting developmental opportunities away from the next generation of experts. Expertise resilience should consequently be assessed across career stages and levels rather than inferred from the continued competence of current senior employees. A resilient workflow would need to sustain present performance while maintaining pathways for future expertise formation, knowledge transfer, error recognition, and independent judgment.

Proposed expertise-resilience framework

The proposed Expertise-Resilience Framework integrates these findings around a distinction between automation configuration, expertise-maintenance mechanisms, and conditional expertise trajectories. Delegation theory clarifies that agentic systems can assume elements of performance and control without making human capability irrelevant; hybrid-intelligence theory emphasizes complementary human and machine contributions; experimental evidence on delegation demonstrates the importance of understanding relative human–AI strengths [28-30]. Together, these literatures support treating retained task exposure, epistemic visibility, calibration, feedback, and reciprocal learning as candidate mechanisms. Their combination into a single expertise-resilience architecture is an original synthesis rather than an empirically validated model.

Figure 2 presents the original conceptual synthesis for expertise-resilience framework, showing how the article's principal constructs, mechanisms, uncertainties, and decision boundaries are connected.

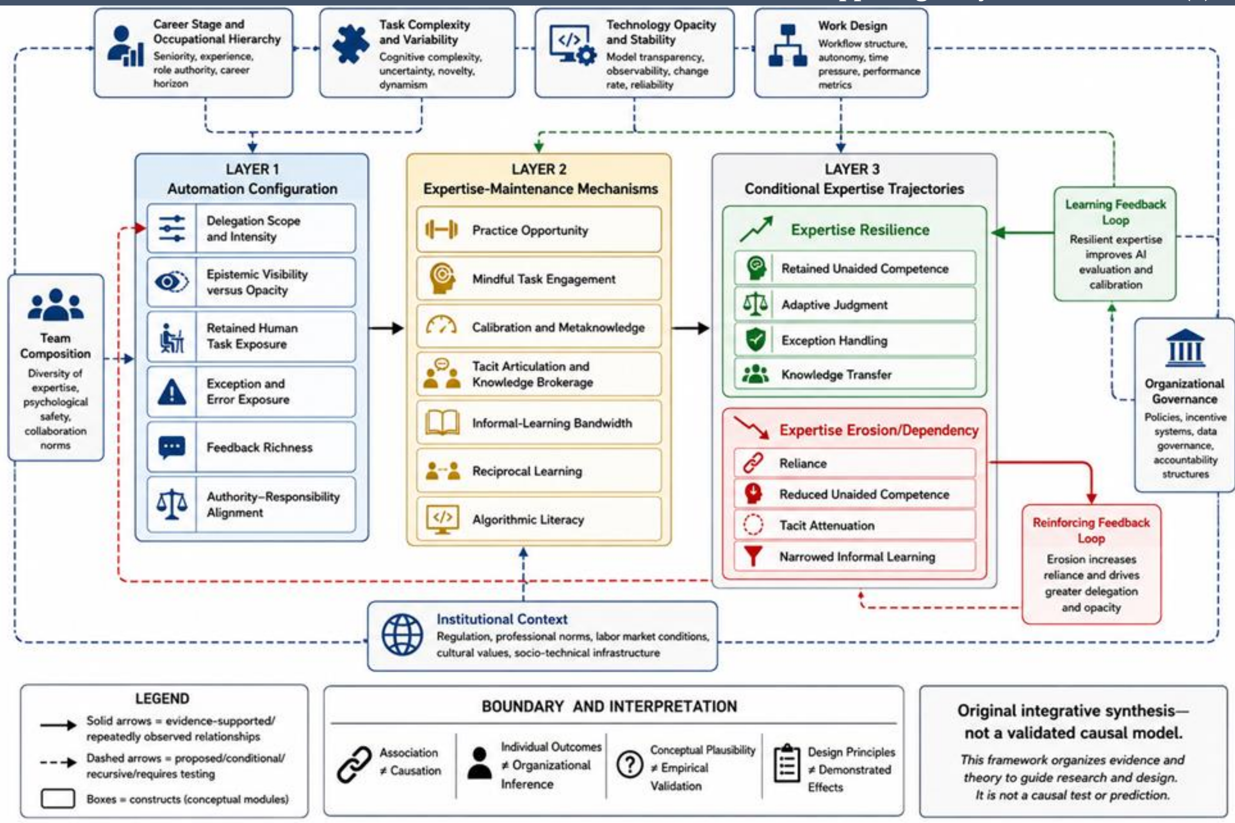

Figure 2. Expertise-Resilience Framework

The framework is explicitly multilevel. AI-related outcomes can differ across individuals, teams, and organizations, making it inappropriate to infer organizational expertise from individual perceptions or short-run productivity alone [31]. Individual resilience concerns retained competence and judgment; team resilience concerns distributed access to complementary knowledge and opportunities for explanation; organizational resilience concerns whether structures sustain expertise formation, knowledge transfer, and informed exception handling. These levels can diverge. A system may improve organizational throughput while weakening individual unaided capability, or preserve senior expertise while reducing junior developmental opportunity.

A system view further implies that expertise resilience emerges from interactions among actors, tasks, technologies, routines, and organizational structures rather than from a single human–AI dyad [32]. The framework therefore proposes two recursive trajectories. Reduced task exposure and increased reliance may progressively weaken practice and evaluation capacity, encouraging further delegation. Conversely, retained expertise may improve employees' ability to evaluate automated outputs, identify exceptions, and calibrate future delegation. These feedback loops remain conceptual integrations requiring longitudinal testing, particularly during automation failure, task change, and periods when employees must operate without assistance.

Table 3 translates the framework's unresolved relationships into a focused research agenda centered on what must be measured, compared, and observed before expertise resilience can be treated as an empirically established organizational phenomenon.

Table 3. Research tests required to evaluate the proposed Expertise-Resilience Framework

Unresolved problem	Why existing evidence is insufficient	Stronger research approach	Critical outcome to observe	Important boundary condition	What would challenge the proposed framework
Does automation reduce unaided competence?	Assisted performance often dominates measurement	Repeated assessment before, during, and after sustained automation exposure	Independent task performance without automated assistance	Task complexity and exposure duration	Stable or improving unaided capability despite extensive delegation
Does reduced task exposure produce skill erosion?	Task removal and competence decline are rarely observed together over time	Longitudinal comparison of workflows with different retained-practice levels	Skill retention, diagnostic accuracy, recovery after system withdrawal	Frequency and quality of manual practice	No relationship between reduced exposure and later independent competence

Is tacit knowledge lost or merely redistributed?	Knowledge visibility and knowledge possession are frequently conflated	Process tracing of knowledge movement across roles before and after automation	Availability, transferability, and enactment of situated knowledge	Brokerage structure and occupational specialization	Successful redistribution without concentration or accessibility loss
Does AI accelerate learning for less experienced workers?	Immediate productivity improvements may not persist independently	Delayed transfer tests comparing assisted and unaided performance	Retention, adaptation to novel cases, explanation quality	Prior expertise and type of AI assistance	Gains disappear once assistance is removed
Can expertise resilience coexist with unequal learning access?	Aggregate organizational outcomes conceal career-stage differences	Multilevel studies following junior and senior workers simultaneously	Distribution of practice, mentoring, task authority, and knowledge transfer	Occupational hierarchy	Organization-level resilience accompanied by persistent developmental exclusion
Which work-design features protect expertise?	Individual design features are usually studied separately	Comparative longitudinal studies of alternative workflow configurations	Continued practice, feedback use, exception handling, learning behavior	Technology opacity and task volatility	Similar expertise outcomes across substantially different work designs
Are the proposed feedback loops real?	Recursive erosion and resilience processes are mainly conceptual	Longitudinal or interrupted-time designs capturing repeated delegation cycles	Changes in reliance, calibration, competence, and subsequent delegation	System reliability and failure frequency	No recursive relationship between retained capability and later automation choices
Can expertise resilience be inferred at organizational level?	Individual performance measures cannot establish collective capability	Multilevel designs connecting individual competence with team and organizational knowledge processes	Redundancy, knowledge transfer, failure recovery, continuity of expertise	Team composition and governance	Strong individual competence without corresponding system-level resilience

Note. The research tests and falsification conditions are original proposals derived from the critical synthesis. They are research priorities rather than validated measures, prescribed interventions, implementation standards, or claims that the proposed framework is correct.

Organizational design and research agenda

Organizational design determines whether delegation to AI merely reallocates tasks or also removes the practices through which employees retain the capacity to understand and challenge those tasks. Research on AI-enabled decision structures, sociotechnical integration, and algorithmic management converges on the importance of how authority, technology, people, and work processes are configured [33-35]. For expertise research, this shifts attention from whether a human formally remains involved to whether that involvement includes meaningful judgment, access to task information, exception handling, feedback, and the ability to alter or contest automated recommendations. Formal permission should therefore be distinguished from substantive influence, just as technical capability should be distinguished from legitimate organizational authority.

The evidence base remains fragmented, and current AI–HRM scholarship identifies the need for stronger longitudinal, multilevel, and context-sensitive research designs [36]. Expertise-resilience research should directly measure unaided performance before and after sustained automation exposure, observe whether skills recover when assistance is removed, and trace how tacit knowledge is transferred across career stages and teams. Comparative studies should vary task volatility, system opacity, error frequency, work design, and governance arrangements. Research should also examine failure episodes, because routine high-performing automation may conceal whether employees retain the knowledge needed to diagnose exceptions. Such studies could test, refine, or reject the proposed framework rather than assuming that its mechanisms are correct.

Conclusion

Automation changes more than the distribution of task execution. It can alter who practices, who sees intermediate reasoning, who encounters exceptions, who learns from whom, and who remains capable when automated assistance is unavailable or wrong. The reviewed literature does not support a deterministic conclusion that automation causes either deskilling or augmentation. Instead, expertise erosion, dependency, redistribution, and resilience appear to be conditional trajectories shaped by task exposure, epistemic visibility, informal learning, calibration, work design, occupational hierarchy, and opportunities for reciprocal learning.

The principal contribution of this Critical Review Article is to connect these domains through the proposed Expertise-Resilience Framework while preserving the limits of the available evidence. The framework treats retained expertise as a work-system property rather than a simple individual possession and distinguishes assisted performance from unaided capability. Its proposed feedback relationships remain unvalidated and should be tested longitudinally, across levels, and under conditions of system failure or withdrawal. The central organizational question is therefore not simply how much work can be automated, but whether automated workflows continue to reproduce the human knowledge and judgment on which resilient performance may ultimately depend.

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