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The Redistribution of Organizational Expertise When Generative Artificial Intelligence Expands Knowledge Production but Concentrates the Burden of Verification

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Abstract

Generative artificial intelligence expands employees' capacity to produce analyses, drafts, recommendations, and other knowledge-intensive outputs, but it does not necessarily expand the organizational capacity to determine which outputs are reliable enough to use. This article develops a multilevel account of that asymmetry. It distinguishes machine-assisted knowledge production from the expertise required to validate, contextualize, challenge, and authorize consequential outputs, and traces how these functions are distributed across individuals, teams, organizations, professions, and institutional settings. The central argument is conditional: generative AI can widen participation in knowledge production while shifting epistemically consequential work toward actors who retain domain knowledge, intervention rights, and accountability. Transparent and standardized tasks, distributed decision rights, supportive work design, and deliberate capability development can diffuse verification capacity; opacity, restricted learning opportunities, and centralized authority can concentrate it. Expertise is therefore treated as an organizationally allocated and reproduced capacity rather than a fixed occupational stock. The resulting theory reframes the issue from whether AI replaces experts to how expert work is redistributed when production and verification scale differently.

Keywords Human–AI collaboration, Generative artificial intelligence, Multilevel theory, Verification, Knowledge work, Organizational expertise

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Introduction

Generative artificial intelligence is frequently discussed as a means of accelerating knowledge work and widening access to analytical production. Its organizational consequences, however, cannot be specified at one level. Multilevel theorizing requires clarity about where constructs reside, how effects travel across levels, and when lower-level changes aggregate into organizational outcomes [1]. This is especially important for generative AI because individual use is embedded in team routines, organizational decision rights, professional standards, and institutional expectations.

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Research on learning algorithms already shows that algorithmic systems can reshape expertise, coordination, and control, while organization theory has identified AI as a source of new task inputs, processes, and outputs [2, 3]. The narrower problem examined here is the possible separation between producing candidate knowledge and determining whether that knowledge is accurate, contextually appropriate, and safe enough to act upon. Human–AI complementarity research indicates that computational and human capabilities remain differentiated where judgment requires contextual or equivocal knowledge [4]. Production capacity therefore cannot be treated as equivalent to epistemic responsibility.

A multilevel review of AI in organizations confirms that relevant effects occur across individual, group, and organizational levels [5]. What remains insufficiently explained is how these levels become coupled when output capacity expands faster than the expertise needed to appraise it. This question differs from whether AI raises productivity, whether users trust algorithms, whether managers remain formally accountable, or whether organizational memory is authentic. Its focus is the organizational distribution of expert work when production and verification do not scale together.

Experimental evidence shows that generative AI can improve performance and reduce completion time on bounded professional writing tasks [6]. Early qualitative evidence on ChatGPT use likewise identifies knowledge-production affordances alongside role and quality side effects [7]. These findings do not establish inevitable verification scarcity. They establish the need to distinguish production expansion from the arrangements through which generated material becomes usable organizational knowledge. The article therefore develops a multilevel theory in which expertise may shift across production, interpretation, verification, escalation, and authorization rather than simply disappear.

Organizational Expertise before Generative AI

Organizational expertise is produced through participation in consequential work. In robotic surgery, technologically mediated practice restricted conventional opportunities for novices to build skill and encouraged “shadow” learning outside approved routes [8]. Expertise is therefore not merely stored in individuals; organizations reproduce it by structuring access to tasks through which judgment is acquired.

Validation work is part of this developmental infrastructure. Anthony showed that black-boxed analytical technologies can separate workers from practices through which outputs are questioned, reconstructed, and validated [9]. When employees receive answers without participating in how those answers are tested, the organization may alter both immediate quality assurance and future expertise development.

Expertise also contains an authority dimension. Algorithm introduction can alter a “regime of knowing,” changing which forms of knowledge become legitimate and actionable [10]. This intersects with broader forms of algorithmic control that redistribute direction, evaluation, and discipline while eliciting worker accommodation or resistance [11]. Consequently, expertise includes not only capability but also recognition and the practical right to influence action.

Organizations already had multiple ways to allocate human and machine participation before generative AI. Human–AI decision structures can involve delegation, sequential combinations, or aggregation [12]. Technical production and decision authority therefore need not be colocated. This baseline complicates simple substitution accounts: automation and augmentation can coexist, because automating one component of work may increase the importance of interpretation, exception handling, coordination, or judgment elsewhere [13]. Generative AI intensifies this established redistribution problem by broadening the range of actors able to produce plausible knowledge outputs.

Expansion of Machine-Assisted Knowledge Production

AI can participate across knowledge creation, retrieval, sharing, and application [14]. Generative systems extend this participation by lowering the effort required to transform prompts and source material into coherent artifacts. The

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immediate organizational change is thus an expansion of candidate knowledge production: more actors can produce outputs that resemble expert work in form.

Yet technology access does not determine productivity by itself. Research on digital assistants shows that productivity-related outcomes depend on how workers interact with the technology and on the surrounding user experience [15]. Employees also interpret AI through expectations about their future roles. Studies of AI-enabled job characteristics and perceived substitution concerns indicate that machine assistance can alter work behavior even before formal responsibilities change [16].

The effects are also position-dependent. Two-wave evidence indicates that job level and job role can moderate AI-related outcomes [17]. Individual production gains may therefore aggregate differently across teams according to who uses the technology, what expertise they already possess, and what downstream work others must perform. Work design provides a mechanism for organizing these differences: automation effects depend on the distribution of demands, resources, autonomy, and opportunities for skill use [18].

AI–employee collaboration further depends on complementary conditions such as skill, knowledge sharing, trust, and role clarity [19]. These determine whether machine-generated material remains an individual aid or enters collective routines with shared interpretation and responsibility. Machine-assisted production is consequently multilevel: individual use can increase candidate output, team processes determine how that output circulates, and organizational arrangements condition how it enters decisions.

These cross-level relations place production growth within a layered system of roles, learning opportunities, and organizational constraints, as shown in **Figure 1.**

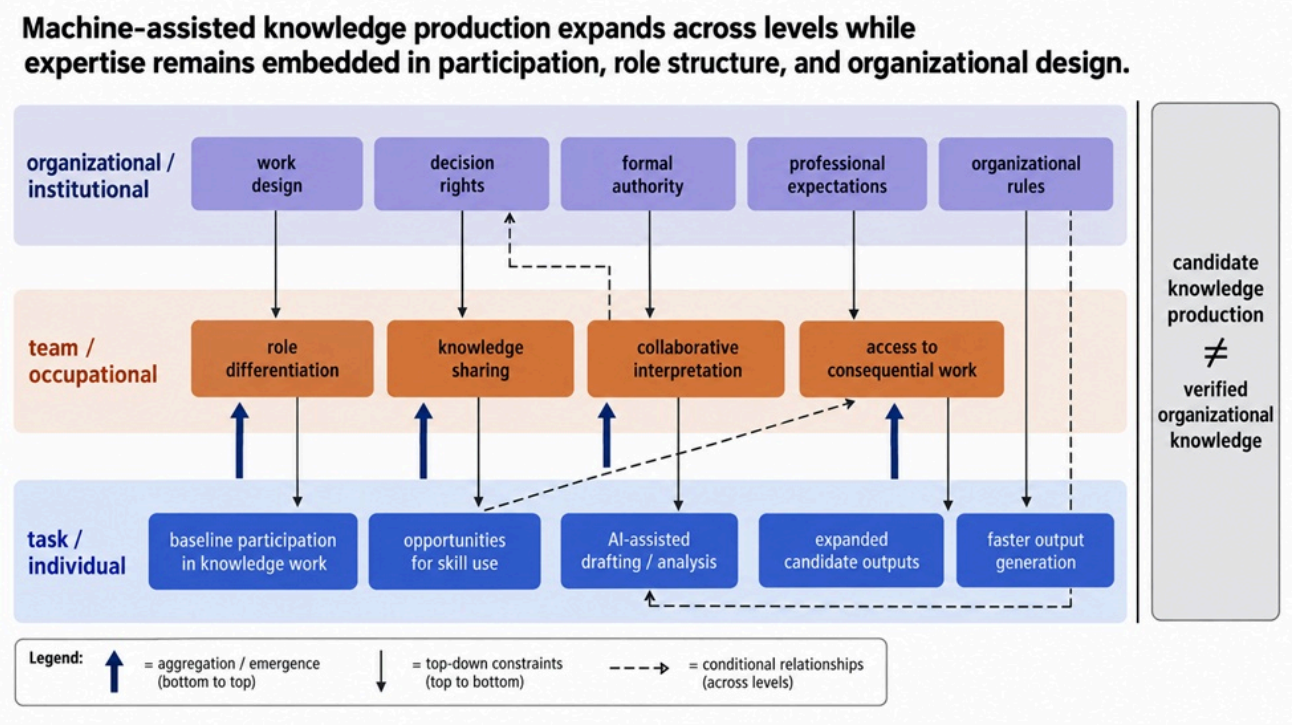

Figure 1. Machine-assisted knowledge production expands across levels while expertise remains embedded in participation, role structure, and organizational design.

Verification as Scarce Expert Work

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Verification is analytically distinct from production. Here it denotes the situated work required to determine whether an output is accurate enough, contextually appropriate, sufficiently complete, and consequentially safe to support action. It includes recognizing uncertainty and exceptions, identifying missing context, and deciding whether an output should be revised, rejected, escalated, or independently reconstructed.

Professional encounters with opaque AI illustrate why such work can remain expertise-intensive. Medical professionals develop different practices for engaging with AI when critical judgments must be made under opacity [20]. The relevant competence is not simply reading an output but deciding when it is credible, when it should be challenged, and how uncertainty affects action.

System design can change this burden. Transparency features can improve evaluability, yet different forms of transparency produce different effects on understanding and trust [21]. Transparency therefore changes the conditions under which expertise can be exercised; it does not eliminate judgment. Nor is human verification a neutral gold standard. Experimental evidence shows that human and algorithmic evaluators can be perceived differently with respect to bias and objectivity [22]. Concentrating review in humans is thus not automatically optimal.

Experience is similarly nonuniform. Domain experience can improve the ability to evaluate algorithmic advice while also increasing reluctance to use it under some conditions [23]. The relevant resource is task-specific competence combined with opportunity and authority to intervene. Interviews with recruitment professionals likewise show that expert interventions depend on professional knowledge, practical understandings of AI, oversight responsibilities, and organizational context [24].

Comparative research on algorithmic knowledge work shows that algorithm use can alter skill requirements, quality-assurance practices, and authority relations [25]. Verification can therefore become scarce even when knowledge production appears abundant: production tools may be broadly available, while contextual competence, accountability, and intervention rights remain unevenly distributed. The resulting distinction is visible in **Table 1**, where different verification tasks impose different combinations of knowledge, organizational access, and intervention rights.

Table 1. Verification work differs by what must be judged, where expertise resides, and which organizational rights permit intervention

Verification work unit	What must be established	Expertise required	Organizational dependency	Failure when production scales faster	Condition for wider distribution
Consistency checking	Claims and internal relations are supportable	Domain knowledge plus evidence access	Access to underlying sources and checking time	Plausible but unsupported outputs enter workflows	Accessible evidence and standardized checks
Contextual fit	Output applies to the specific case or environment	Situated experience	Proximity to operating context	Generic outputs are treated as locally valid	Shared contextual knowledge
Exception recognition	Nonroutine conditions invalidate routine recommendations	Pattern knowledge from unusual cases	Exposure to exceptions and learning opportunities	Rare consequential cases are missed	Deliberate exposure and escalation channels
Consequence appraisal	Acting on the output does not create	Domain judgment plus	Visibility into responsibility and effects	High-volume output crowds	Shared responsibility and

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	unacceptable downstream risk	consequence knowledge		out low-frequency risks	consequence information
Challenge and override	Output should be revised, rejected, or replaced	Technical and professional judgment	Formal intervention rights	Review becomes symbolic	Authority accompanies competence
Escalation/reconstruction	Uncertainty requires referral or analysis from first principles	Integrative expert reasoning	Access to senior expertise, time, and alternative methods	A small group becomes the terminal queue	Multiple actors can reconstruct, not merely inspect, reasoning

Redistribution Rather Than Elimination of Expertise

Once verification is separated from production, AI appears less as a uniform eliminator of expertise than as a force that can relocate expert work. Professions research on AI and academic library work suggests that new technologies may alter competencies, jurisdictional claims, and divisions of professional labor without implying disappearance of the profession itself [26]. The theoretical issue is therefore which activities continue to require expert discretion and which become accessible to a wider set of actors or systems.

Field evidence likewise shows that experience is differentiated rather than uniformly devalued. In AI-assisted medical coding, task-specific experience and broader work experience were associated with different patterns of productivity and trust [27]. Some forms of experience may become more valuable because they support evaluation or exception handling, even as routine production becomes easier.

Organizational design translates these differences into roles. Human–AI collaboration depends on choices concerning substitution, diversity, collaboration, and explanation rather than on technical capability alone [28]. These choices influence whether machine-assisted production is paired with distributed evaluative capability or a narrower group of reviewers. Consistent with the automation–augmentation paradox, automation of one component can raise the relative importance of another [13].

A junior employee may therefore become able to produce a first-pass analysis that previously required more senior labor, while evaluation of unusual assumptions, missing evidence, or downstream consequences remains with senior specialists. Expertise has moved from initial production toward interpretation, verification, and authorization. Redistribution can also be horizontal: teams may divide review across complementary specialists, or organizations may create dedicated validation functions.

Redistribution is not identical to concentration. It denotes a change in the location or content of expert work. Concentration occurs only when consequential verification repeatedly accumulates around a restricted set of actors or organizational positions. Generative AI can therefore democratize one layer of knowledge production while centralizing another, but it need not do so. Work design, learning access, contextual knowledge, and intervention rights can also distribute verification capability. The next section explains the conditions under which redistribution becomes diffusion, specialization, or a verification bottleneck.

Verification Bottlenecks and Expertise Concentration

Redistribution becomes concentration when the organization expands the number of actors able to produce plausible knowledge faster than it expands the number able and authorized to evaluate that knowledge. Evidence from AI-enabled knowledge-management processes suggests that AI use, knowledge processes, and organizational decision making can

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develop reciprocal rather than purely linear relationships [29]. Verification capacity may therefore become both an input to and a consequence of AI-enabled work design.

A verification bottleneck arises when candidate outputs arrive faster than qualified reviewers can reconstruct assumptions, examine evidence, recognize exceptions, and assess consequences. Experimental evidence that generative AI can accelerate bounded knowledge production [6] and qualitative evidence concerning its organizational side effects [7] support the production side of this asymmetry. The bottleneck itself is a theoretical synthesis: it is not established by a single study and should not be assumed wherever generative AI is used.

Concentration also depends on authority. Expert knowledge is insufficient when knowledgeable employees lack permission to challenge, modify, or block AI-supported outputs. Recruitment professionals' interventions in AI recommendations, for example, depend partly on oversight arrangements and organizational context [24]. A nominally distributed workforce may therefore possess considerable evaluative competence while practical verification remains concentrated in a narrow group holding formal intervention rights.

The temporal consequence may be more important than the immediate queue. Restricted participation in consequential work can weaken opportunities for developing expertise [8]. If organizations repeatedly route difficult verification to a small specialist group, junior and peripheral actors may lose exposure to the cases through which judgment develops. Present concentration can then reduce future verifier supply, tightening the same constraint that initially produced concentration. This feedback is conditional: deliberate apprenticeship, distributed escalation rights, and work designs that preserve participation can interrupt it.

Expertise Redistribution Framework

The resulting theory distinguishes **p**roduction capacity from verification capacity. Production capacity concerns the ability to generate candidate analyses, explanations, recommendations, or other knowledge artifacts. Verification capacity concerns the ability to judge whether those artifacts are sufficiently accurate, contextualized, complete, and consequentially acceptable for use. The two capacities may rise together, but they need not do so.

Their organizational location depends on three conditions. The first is competence: whether actors possess the domain and contextual knowledge required to evaluate an output. The second is intervention authority: whether they can reject, revise, escalate, or override that output. The third is evaluability: whether the system and task expose enough information for meaningful appraisal. Human–AI decision structures demonstrate that decision rights can be configured in multiple ways [12], while transparency research shows that system design changes the conditions under which evaluation occurs [21].

These conditions generate several possible organizational states. Production and verification may both remain concentrated among specialists; production may diffuse while verification stays concentrated; both may diffuse when competence and rights are broadly distributed; or verification may become specialized across several complementary roles without being centralized in a single hierarchy. Variation by job level and role [17] and by forms of experience [27] makes a single deterministic trajectory implausible.

Redistribution is also dynamic. Validation practices can create or remove opportunities for learning [9], while work design changes the resources and demands attached to technology use [18]. Current allocation decisions can therefore change the future stock and distribution of organizational expertise. **Table 2** formalizes these configurations without assuming that one state is universally preferable.

Table 2. Alternative expertise-distribution states produced by different alignments of production reach, verification capability, and intervention rights

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Organizational state	Production reach	Verification capability	Intervention rights	Immediate pattern	Longer-horizon expertise implication
Specialist concentration	Restricted	Concentrated	Concentrated	Experts both produce and verify consequential outputs	Deep expertise retained but access remains narrow
Production diffusion with verification concentration	Broad	Uneven	Concentrated	Many actors generate outputs; few authorize their use	Reviewer queues may grow and learning access may narrow
Distributed verification	Broad	Broad enough for task	Distributed with escalation	Production and routine checking occur close to work	Expertise may develop across more roles
Complementary specialization	Broad	Distributed across distinct specialties	Shared or sequential	Different experts validate different dimensions	Expertise diversifies rather than centralizes
Symbolic decentralization	Broad	Broad or moderate	Restricted	Employees can inspect but cannot meaningfully intervene	Apparent participation does not equal epistemic authority
Reproductive concentration	Broad	Initially concentrated	Concentrated	Difficult cases repeatedly return to the same experts	Future verifier supply may weaken unless learning access is protected

Propositions

The framework yields discriminating propositions that distinguish redistribution from simple automation.

Proposition 1. When machine-assisted production capacity grows faster than qualified verification capacity, verification work will shift toward actors already possessing domain knowledge and consequence-bearing responsibility. Evidence that algorithmic knowledge work can redistribute quality-assurance responsibilities supports the underlying allocation mechanism [25].

Proposition 2. The tendency toward verification concentration will be stronger when outputs are difficult to evaluate, tasks are consequential, and system opacity limits inspection. Professional responses to opaque AI demonstrate that critical judgment practices become especially important under such conditions [20].

Proposition 3. Verification concentration will be weaker when competence, evidence access, and meaningful intervention rights are distributed close to the point of use. Research on AI–employee collaboration shows that skills, knowledge sharing, trust, and role clarity condition effective collaboration [19].

Proposition 4. Repeated concentration of consequential verification will reduce future organizational verification capacity when it deprives less-experienced actors of participation in expert judgment. Evidence on shadow learning establishes the broader mechanism through which restricted participation can disrupt expertise development [8].

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Proposition 5. Diffusion of AI-assisted production will not constitute diffusion of organizational expertise when authority to challenge, revise, or reject outputs remains centralized. Research on changing regimes of knowing shows that practical epistemic authority can be redistributed independently of access to information or tools [10].

Proposition 6. Transparent, standardized, and lower-consequence tasks will be more compatible with distributed verification than opaque, context-sensitive, and high-consequence tasks. Human–AI complementarity theory provides the basis for expecting different allocations as task conditions change [4].

Together, these propositions make the theory falsifiable. Evidence that production expansion routinely increases verification capability at the same rate, or that intervention authority has no bearing on where evaluative work accumulates, would weaken the central account.

The conditional pathways are summarized in **Figure 2.**

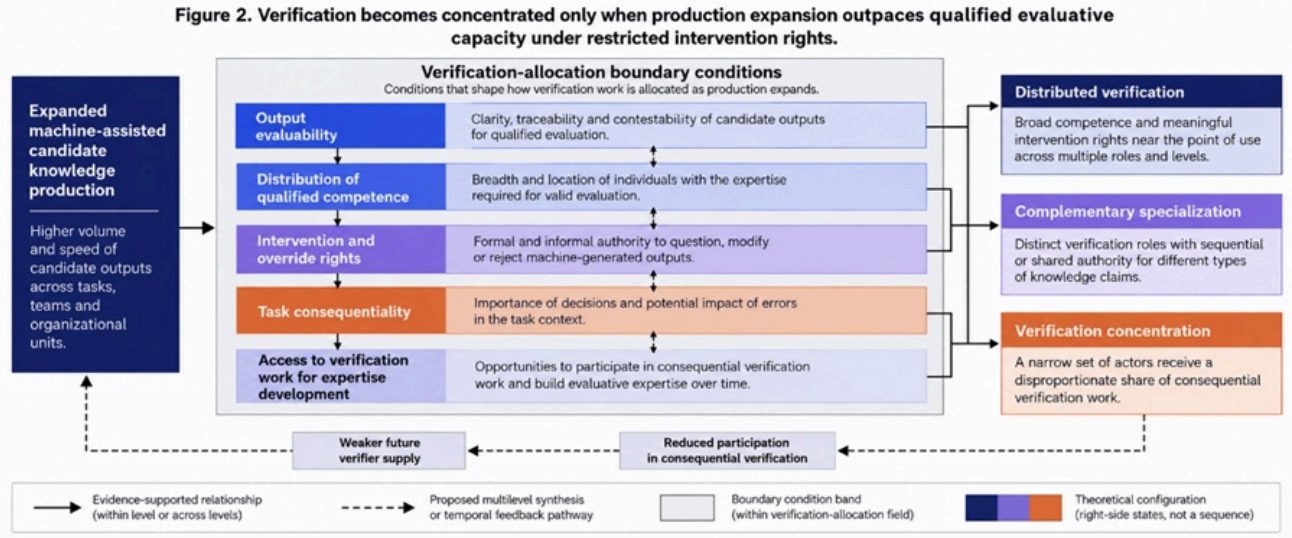

Figure 2. Verification becomes concentrated only when production expansion outpaces qualified evaluative capacity under restricted intervention rights.

Organizational Implications

Organizations adopting generative AI should assess production and verification capacity separately. Counting users, generated outputs, or automated tasks reveals little about whether sufficient evaluative capability exists downstream. Work-design research indicates that digital technology outcomes depend on how demands, resources, autonomy, and opportunities for skilled work are configured [18].

Second, expertise should be aligned with meaningful intervention rights. A worker who can identify an erroneous recommendation but cannot halt or revise it adds little practical verification capacity. Expert intervention research shows that oversight structures and organizational context shape how professionals engage with AI-supported decisions [24]. Governance should therefore distinguish access to AI from authority over AI-mediated action.

Third, organizations should treat verification as part of expertise development. If difficult cases are consistently routed upward, central review may improve short-run consistency while shrinking the number of actors who learn how to exercise consequential judgment. Validation work should therefore be designed not only as quality control but also, where feasible, as supervised participation through which expertise is reproduced [9].

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Finally, evaluation should distinguish immediate productivity from long-horizon expertise resilience. Early generative-AI use demonstrates that productivity affordances can coexist with quality and role side effects [7]. A locally efficient arrangement may thus create a future dependency if it removes too much evaluative work from those expected eventually to become expert reviewers.

Conclusion

Generative AI can expand organizational knowledge production without producing an equivalent expansion in the capacity to judge what should be trusted, revised, rejected, or escalated. The resulting organizational change is best understood as a redistribution problem. Production, verification, interpretation, authorization, and learning may move to different actors and levels.

Verification concentration is therefore a conditional outcome rather than an intrinsic property of generative AI. It becomes more plausible when output volume expands rapidly, evaluability is weak, competence is unevenly distributed, consequential decisions require contextual judgment, and intervention rights remain centralized. It becomes less plausible when organizations distribute both capability and authority, preserve participation in consequential verification, and design transparent processes that permit routine evaluation close to the point of use.

The theoretical consequence is that expertise should not be inferred from who produces knowledge artifacts. In AI-enabled organizations, the more revealing question is who retains the capacity and permission to determine whether those artifacts are usable. Generative AI may democratize production while simultaneously narrowing practical epistemic authority, but organizational design determines whether that separation persists. The durability of AI-enabled knowledge production will therefore depend partly on whether organizations expand verification capability and reproduce expertise at the same time that they expand machine-assisted output.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 29 Dec 2022 Revised: 05 Mar 2023 Accepted: 21 Mar 2023
Published online: 18 March 2024

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