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Work Redesign after Digital Augmentation of Human Expertise and Agency

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Abstract

Digital augmentation increasingly changes not only how work is performed but also who exercises judgment, how expertise develops, and when workers rely on technological recommendations. Existing scholarship often treats these outcomes separately or frames artificial intelligence primarily as automation, obscuring the organizational design choices through which human and technological contributions are combined. This integrative review examines how digital augmentation reshapes work through four connected domains: human agency, expertise development and erosion, trust in human–technology collaboration, and work-redesign configurations. The review combines theoretical, qualitative, experimental, field, and multilevel evidence while preserving differences in design, context, and inferential strength. Across the literature, augmentation does not emerge as a uniform condition. Human discretion can coexist with strong algorithmic control; short-term performance gains may accompany uncertain long-term skill trajectories; and reliance on artificial intelligence can support judgment while also creating risks of overreliance, knowledge convergence, or diminished developmental participation. The review therefore proposes that digital work redesign should be analyzed through configuration-specific allocations of authority, learning opportunity, and reliance rather than through technology labels alone. The resulting synthesis identifies organizational implications for accountability, participation, and capability development, while emphasizing that context, task structure, expertise, opacity, and level of analysis constrain transferability. The proposed framework is an organizing synthesis rather than a validated causal model and requires longitudinal, comparative, and multilevel testing.

Keywords: Human agency across augmentation modes, Expertise development and erosion, Trust in human–technology collaboration, Work-redesign configurations, Future research, Redesign

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Introduction

Digital augmentation changes the architecture of work because technological systems increasingly influence not only task execution but also the motivational, knowledge, social, and contextual properties through which jobs are experienced and coordinated [1]. Work redesign is therefore a more precise analytical problem than technology adoption alone. The central question is not simply whether artificial intelligence replaces or assists workers, but how technological capabilities become embedded in task boundaries, information flows, discretion, monitoring, collaboration, and opportunities to learn. These changes can redistribute agency without eliminating human involvement and can alter expertise even when immediate performance improves.

The distinction between automation and augmentation is itself unstable. Artificial intelligence may substitute for some human activities while simultaneously increasing the importance of human interpretation, exception handling, or coordination, creating an automation–augmentation paradox rather than a simple continuum [2]. Learning algorithms further complicate this framing because their role in organizations is not limited to executing fixed instructions; they can participate in evolving processes of knowledge production and organizing [3]. At the same time, algorithmic systems can become mechanisms of direction, evaluation, and control, making questions of worker discretion and contestation integral to digital work design [4].

A broader digital-transformation perspective reinforces the need to move beyond isolated task effects. Digital technologies can become entangled with changes in organizational structures, processes, and value creation, meaning that redesigned work is situated within wider organizational transformation [5]. Yet the literature remains heterogeneous. Studies differ in occupation, technology, unit of analysis, temporal horizon, and whether they examine perceived autonomy, observable behavior, task performance, learning, trust, or formal authority. These differences limit simple generalization.

This article therefore uses an integrative review to connect evidence on agency, expertise, trust, and work-redesign configurations. Its contribution is to identify where findings converge, where they conflict, and where apparently positive augmentation outcomes depend on conditions that are often left implicit. The review separates short-term performance from expertise development, reliance from calibrated trust, formal decision rights from enacted discretion, and technological capability from legitimate authority. It then develops an original digital work-redesign framework that organizes these relationships without claiming causal validation or universal applicability.

Integrative review method

The review followed an integrative design in which literature synthesis was treated as an explicit research methodology rather than as a narrative accumulation of sources [6]. Search concepts covered digital augmentation, work redesign, human agency, expertise, trust, human–technology collaboration, algorithmic management, human-in-the-loop configurations, organizational decision structures, and methodological terms relevant to integrative synthesis. Eligible sources were peer-reviewed journal articles with verified DOI records, relevant journal standing, and direct applicability to at least one review claim, structured evidence element, methodological decision, limitation, or research priority.

Transparent review practice requires explicit decisions about search, selection, extraction, comparison, and reporting [7]. DOI normalization produced 47 unique candidate articles for screening. Five were excluded at title and abstract, leaving 42 reports for eligibility assessment; none was unavailable. Eight were excluded after eligibility assessment: four for redundant construct or contextual evidence, three because stable final bibliographic metadata were unavailable, and one for insufficient direct fit. The final synthesis therefore contained 34 eligible sources. Extraction preserved study purpose, design, unit, context, focal construct, mechanisms, outcomes, limitations, and transferability boundaries. Heterogeneous evidence was compared across domains without treating unlike designs as quantitatively commensurable.

PRISMA-compatible reporting was used only to document selection flow [8]. It does not change the declared integrative-review design or establish exhaustive coverage.

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

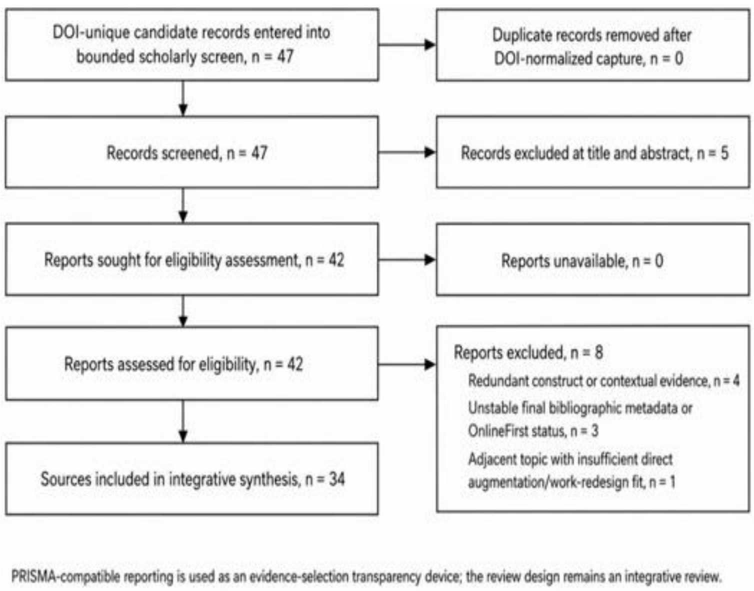

Figure 1. PRISMA Flow Diagram for Evidence Identification and Selection

The figure reports the evidence-identification and selection process used for "Work Redesign After Digital Augmentation of Human Expertise and Agency." Every numerical value and exclusion reason was generated and verified during Part 1. The diagram is a reporting device and does not change the declared review design or establish exhaustive coverage.

Human agency across augmentation modes

Human agency in augmented work is best understood as relational rather than as a fixed quantity possessed exclusively by either workers or technologies. Conjoined-agency theory shows that organizational action may emerge through different forms of coupling between human and technological contributions [9]. This reframes the question from whether humans remain "in control" to which forms of judgment, discretion, adaptation, and consequential authority remain available to them under a given configuration.

Empirical work also cautions against equating algorithmic power with complete human passivity. In online work settings, strong power asymmetries can coexist with worker efforts to interpret, adapt to, and strategically respond to algorithmic structures [10]. Such agency is constrained and should not be mistaken for equal bargaining power or formal autonomy. Conversely, human involvement does not necessarily mean that technology is merely supportive. Human-in-the-loop arrangements may require continuing human work that augments algorithmic functioning, making human activity constitutive of the technological system rather than external to it [11].

Platform research similarly shows that algorithmic matching can be intertwined with mechanisms of control that structure access, evaluation, and discretion [12]. Taken together, these studies suggest that augmentation modes should be distinguished by how judgment, execution, coordination, monitoring, and exception authority are allocated. A nominally "human-in-the-loop" arrangement may preserve meaningful discretion, transfer responsibility without corresponding power, or enlist workers mainly to maintain algorithmic performance. The available evidence therefore supports configuration-sensitive analysis, not a universal scale in which greater automation necessarily means less agency.

Table 1 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for review design, evidence domains, and extraction framework for work redesign after digital augmentation of human expertise and agency.

Table 1. Review design, evidence domains, and extraction framework for Work Redesign After Digital Augmentation of Human Expertise and Agency.

Evidence Domain or Review Construct	Review Question	Eligible Evidence Type	Extraction Fields	Appraisal or Relevance Criterion	Synthesis Role	Main Limitation	Interpretation Boundary
Digital Augmentation and Work Redesign	How does technology alter task, knowledge, control, and organizational structures?	Work-design, organizational, and review evidence	Technology role; work characteristic; level; outcome	Direct connection to work structure or organizing	Establish redesign problem	Broad technologies and contexts	Technology adoption does not itself establish work outcomes
Integrative Review Method	How should heterogeneous evidence be combined transparently?	Review-method and reporting guidance	Search; eligibility; extraction; synthesis; reporting	Method directly supports declared review design	Structure review procedure	No substantive AI evidence	Transparency does not imply exhaustive coverage
Human Agency	How is consequential discretion allocated in human–technology arrangements?	Conceptual and field evidence	Judgment; discretion; adaptation; authority; control	Agency must be observable or theoretically specified	Compare augmentation modes	Context-specific configurations	Agency is not equivalent to formal autonomy or equal power
Expertise Trajectory	How might augmentation change learning opportunity and skill use?	Empirical or theoretical evidence	Participation; task exposure; learning opportunity; expertise use	Must distinguish performance from development	Guide later cross-domain synthesis	Long-term measures often absent	Short-run output cannot establish durable upskilling or erosion
Trust Calibration	When is reliance on technological advice warranted or problematic?	Experimental, field, and review evidence	Reliance; advice quality; expertise; task context	Must separate trust attitude from decision behavior	Connect collaboration to judgment	Measures and contexts vary	More reliance is not necessarily better calibrated reliance

Work-Redesign Configuration	Which actor allocates, executes, monitors, evaluates, or retains exception authority?	Job-design, organizational, and collaboration evidence	Task allocation; control; coordination; decision rights	Must specify actual authority rather than technology label	Organize configuration comparison	Categories require validation	Proposed configurations are analytical, not ranked prescriptions

Expertise development and erosion

Digital augmentation can alter expertise by changing participation in the work through which skill is acquired, maintained, and exercised. Evidence from robotic surgery shows that technologically mediated work arrangements can reduce legitimate opportunities for novice participation, prompting informal forms of "shadow learning" when approved participation is insufficient for skill development [13]. The mechanism is not automation alone; training structures, role allocation, and access to consequential practice shape whether technology becomes a developmental resource or a barrier.

Performance evidence points in a different but compatible direction. In a randomized study of professional writing tasks, access to generative artificial intelligence improved short-run task performance on the activities examined [14]. Workplace evidence from customer support likewise indicates that generative AI assistance can raise productivity and quality, with larger gains among less experienced or lower-performing workers [15]. These findings are consistent with knowledge diffusion and performance augmentation, but they do not establish durable expertise acquisition. Faster or better output can arise because workers learn, because the system supplies missing knowledge, or because task demands are partially externalized.

Opacity further complicates the expertise trajectory. Professionals using AI for critical diagnostic judgments varied in whether and how they engaged with opaque recommendations, showing that expertise shapes interaction with technological advice rather than merely being replaced by it [16]. Across these studies, the most defensible conclusion is therefore conditional: digital augmentation may support performance, redistribute access to knowledge, or restrict developmental participation depending on configuration and context. Expertise development and expertise erosion should consequently be evaluated over time and separately from immediate productivity, because neither short-term gains nor reduced participation alone establishes a stable long-term skill trajectory.

Trust in human–technology collaboration

Trust is consequential in augmented work because technological recommendations matter only through patterns of attention, interpretation, acceptance, verification, or rejection. Evidence across human–AI settings indicates that trust is shaped by characteristics of the user, system, task, and environment rather than functioning as a single stable attitude [17]. For work redesign, the relevant issue is therefore calibrated reliance: whether workers depend on technological input to an extent warranted by its capabilities and by the consequences of the decision.

Experimental evidence also complicates assumptions that people consistently resist algorithms. Algorithm appreciation can occur, but willingness to follow algorithmic judgment changes with comparison targets, including whether the alternative is one's own judgment or that of another person with relevant expertise [18]. Reliance is therefore neither simple acceptance nor resistance. It is conditional on how expertise and advisory authority are perceived.

A further tension arises between individual and collective consequences. AI advice can improve individual accuracy while increasing convergence and reducing unique human knowledge, creating circumstances in which an individually useful aid may weaken informational diversity [19]. Controlled evidence similarly shows that inaccurate advice can reduce decision accuracy regardless of whether it is described as AI-generated or human-generated, while expertise affects how advice is evaluated [20]. AI assistance can improve immediate individual decision performance while still creating problematic reliance or collective-knowledge consequences when advice is poor or responses converge [19, 20].

For organizational analysis, the source of apparent "distrust" must also remain uncertain. Verification or override may reflect appropriate professional skepticism, accountability obligations, stronger domain knowledge, or poor interface design rather than generalized resistance to AI. Conversely, rapid acceptance may reflect time pressure, limited opportunities to inspect system reasoning, or transferred responsibility rather than well-calibrated confidence. The review therefore treats observed reliance as behavior requiring contextual interpretation, not as a direct measure of either trustworthiness or trust.

These findings do not establish that higher trust is preferable. They instead support distinguishing warranted reliance from under-reliance and over-reliance and examining how work design preserves opportunities to question, override, and learn from technological advice.

Table 2 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for cross-study findings, mechanisms, convergence, and conflict in work redesign after digital augmentation of human expertise and agency.

Table 2. Cross-study findings, mechanisms, convergence, and conflict in Work Redesign After Digital Augmentation of Human Expertise and Agency.

Construct, mechanism, or relationship	Representative context	Reported finding	Evidence design	Convergent evidence	Conflicting evidence	Methodological concern	Review interpretation
Conditional trust	Multiple human–AI settings	Trust varies with human, system, task, and environment [17]	Empirical review	Reliance is context-sensitive	No uniform direction	Heterogeneous measures	Treat trust as calibrated reliance
Algorithm appreciation	Judgment tasks	Algorithmic advice may be preferred, conditionally [18]	Experiments	Algorithms can attract reliance	Preference changes with comparison target	Short experimental horizons	Avoid universal aversion/appreciation claims
Knowledge convergence	AI-assisted decisions	Advice may improve individual accuracy while reducing unique knowledge [19]	Model, experiments, simulation	Immediate benefits can coexist with collective costs	Collective effects depend on advice structure	Task-specific evidence	Separate individual from collective outcomes
Advice accuracy	Clinical decision aids	Bad advice reduces accuracy regardless of stated source [20]	Experiment	Advice quality matters	Expertise changes evaluations	Clinical transfer boundary	System label is insufficient for warranted trust
Cross-domain synthesis	Augmented judgment	Agency, expertise, and reliance interact	Mixed evidence above	Multiple pathways converge	Contexts remain heterogeneous	No common effect metric	**Proposed synthesis:** evaluate configuration, not trust alone

Work-redesign configurations

Digital augmentation becomes organizationally consequential through configurations that allocate tasks, information, monitoring, and authority. Algorithmic management can itself operate as a work designer because systems may assign, schedule, direct, evaluate, or otherwise influence characteristics conventionally shaped by managers [21]. The implication is not that algorithms uniformly degrade or enrich jobs, but that their managerial functions should be analyzed as design inputs. A complementary perspective emphasizes human–AI symbiosis, in which computational and human capabilities may be allocated differently according to task characteristics [22]. This possibility is conditional rather than inherently superior: complementarity depends on what each party can contribute and on whether workers retain the contextual judgment needed to recognize technological limits. At the organizational level, decision structures can distribute decision preparation, recommendation, execution, and authority between humans and AI in different ways [23]. At team level, treating machines as collaborators raises additional problems of role definition, communication, coordination, and adaptation [24].

These literatures support a configuration approach. Digital work redesign can operate simultaneously through job-level managerial functions, organizational decision-right allocation, and team-level human–AI roles [21, 23, 24]. Four analytically distinct configurations are therefore carried forward: human-led advisory augmentation; reciprocal human-in-the-loop augmentation; algorithmically coordinated work; and delegated automation with human oversight. These are proposed synthesis categories rather than empirically ranked types. Formal human presence also cannot be equated with substantive power: a worker may retain nominal approval while lacking information, time, or practical ability to contest a system.

Configuration classification also requires separating four dimensions that are often collapsed: who performs the task, who generates the recommendation, who possesses formal decision authority, and who can practically challenge or reverse an outcome. These dimensions may diverge. A human sign-off requirement, for example, preserves formal authorization but not necessarily meaningful discretion if the system structures the available information or if organizational routines discourage overrides. The proposed categories consequently describe distributions of work and authority rather than simple levels of automation.

Table 3 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for contextual moderators, boundary conditions, and organizational implications.

Table 3. Contextual moderators, boundary conditions, and organizational implications.

Context or level	Moderator or boundary condition	Evidence pattern	Organizational implication	Alternative explanation	Transferability limit	Uncertainty	Research need
Platform work	Algorithmic control and market dependence	Agency persists under asymmetric control [10]	Preserve meaningful contestability	Workers adapt strategically	Platform institutions differ	Degree of substantive discretion	Compare employment regimes

Professional learning	Access to consequential practice	Reduced participation can disrupt skill development [13]	Protect developmental task exposure	Training structure may drive effect	Robotic surgery	Long-term skill trajectory	Longitudinal learning measures
Generative-AI work	Prior experience and task	Benefits can differ by experience [15]	Avoid assuming uniform augmentation	Process or selection differences	Customer support	Durability of gains	Track skill after assistance changes
Job design	Algorithmic managerial function	Algorithms can reshape job characteristics [21]	Examine tasks and authority jointly	Implementation varies	Algorithmic-management settings	Direction of effects	Configuration comparisons
Decision structure	Allocation of human/AI authority	Multiple structures are possible [23]	Make escalation rights explicit	Capability changes over time	Decision contexts	Appropriate allocation	Compare decision architectures
Team collaboration	Role and coordination design	AI creates unresolved teamwork dualities [24]	Specify coordination responsibilities	"Teammate" framing may vary	Team settings	Emergent team effects	Multilevel longitudinal research

Proposed digital work-redesign framework

A work-redesign framework must explain not only the designed capabilities of intelligent technologies but also how those capabilities are enacted in situated practice. Scholarship on intelligent technologies cautions against limiting analysis to design and use categories detached from ongoing organizational work [25]. A sociotechnical perspective similarly indicates that AI integration depends on interactions between technical and social arrangements rather than technological performance in isolation [26]. Relational theorizing goes further by locating technological consequences in evolving relations among technologies, people, routines, and organizational structures [27]. Reviews of workplace AI additionally show why affected actors must be distinguished: automation and augmentation can have different implications for workers directly targeted by algorithmic decisions and for observers of those decisions [28].

The proposed Digital Work-Redesign Framework consequently links three conditions—task properties, technology properties, and organizational governance—to four augmentation configurations. Each configuration redistributes agency, alters opportunities for expertise development or erosion, and creates conditions for calibrated or miscalibrated reliance. These channels then shape task composition, coordination, monitoring, learning opportunities, and decision rights. Feedback from errors, performance, learning, resistance, and changing technological capability may prompt redesign of the configuration itself.

The framework does not assume a linear progression from human-led work toward automation. Nor does it treat augmentation as inherently protective of expertise or agency. Its central proposition is configurational: similar technologies may produce different work arrangements when authority, learning opportunities, and review mechanisms differ. Conversely, different technologies may generate similar redesign problems when they redistribute comparable forms of judgment or control.

Three decision boundaries constrain the framework. First, association between a configuration and a worker response does not establish causation because selection, occupation, leadership, or implementation quality may explain the pattern. Second, individual experiences cannot establish team or organizational consequences without cross-level evidence. Third, a design principle such as contestability should not be treated as a demonstrated performance intervention. These boundaries are integral to the framework because redesign choices can change as organizations learn about failures, capabilities, and unintended effects.

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

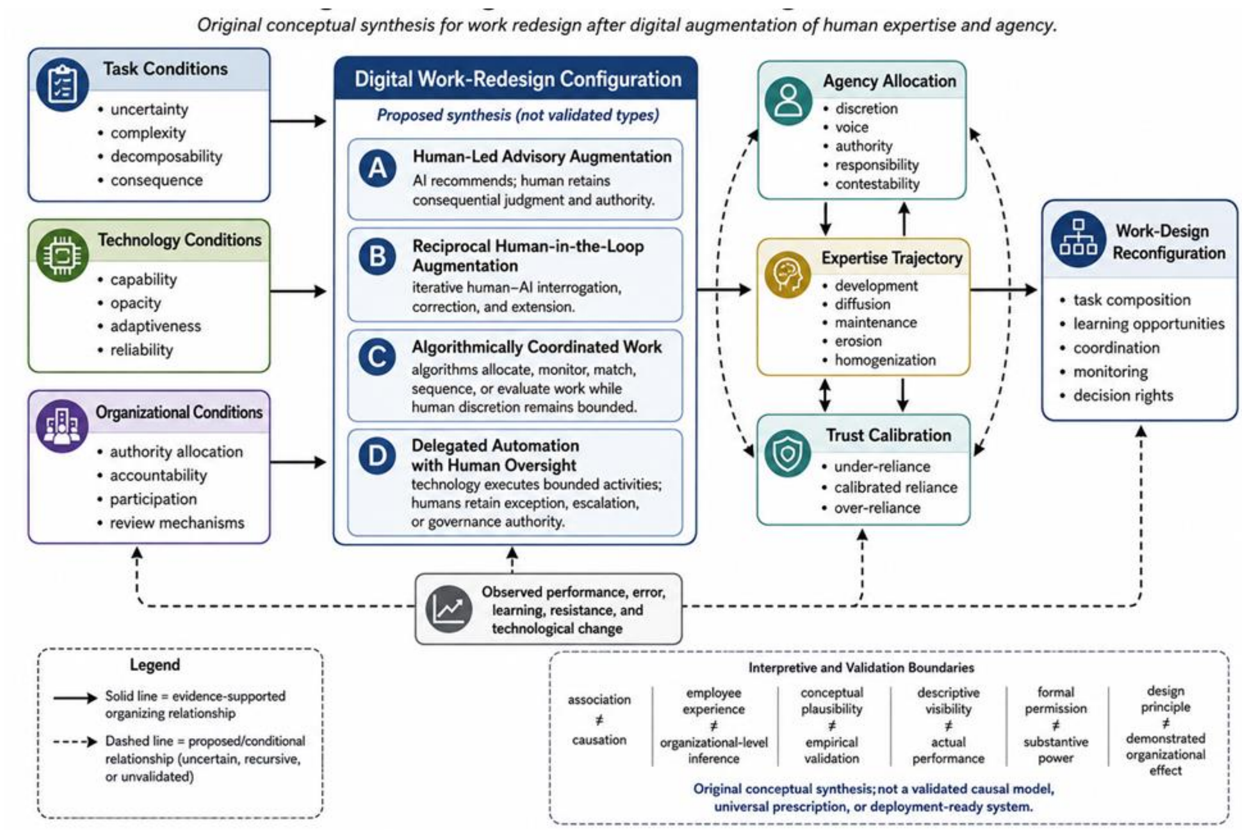

Figure 2. Digital Work-Redesign Framework

The figure is an original conceptual synthesis developed for “Work Redesign After Digital Augmentation of Human Expertise and Agency.” Arrows and grouping indicate evidence-supported or proposed relationships rather than measured effect sizes. The figure does not represent a validated causal model, universal organizational prescription, regulatory determination, or deployment-ready system.

Organizational implications

The synthesis suggests that organizational attention should shift from whether AI is present to how work, authority, and learning are configured around it. In HRM, AI implementation is constrained by data quality, complexity, institutional context, and organizational process, making experimentation and context sensitivity more defensible than assumptions of frictionless technological substitution [29]. These constraints also imply that observed system performance cannot by itself establish that redesigned work is legitimate or sustainable.

Consequential algorithmic decisions raise an additional question of personal integrity. When workers are rendered primarily as data inputs or lack intelligibility and meaningful participation in decisions affecting them, algorithmic HR arrangements may threaten conditions for self-directed action [30]. This argument identifies an ethical boundary; it does not establish the prevalence or magnitude of harm across organizations. Related work on ethical algorithmic HR decision making emphasizes the need to incorporate accountability into decision architecture rather than treat ethics as an external correction after deployment [31].

Consequential HR AI governance should combine organizational accountability with safeguards responsive to employee interests and integrity rather than rely on technical performance alone [29–31]. In the proposed synthesis, this means examining substantive decision authority, mechanisms for contestation and escalation, access to developmental work, and the capacity to verify or override technological recommendations. These are design principles requiring contextual evaluation, not a standardized implementation package.

Table 4 organizes the evidence, constructs, relationships, uncertainties, and boundary conditions required for evidence limitations, unresolved questions, and future research priorities.

Table 4. Evidence limitations, unresolved questions, and future research priorities.

Evidence gap	Why it matters	Current limitation	Required design	Measurement priority	Comparative context	Interpretation safeguard	Future research question

Performance versus expertise	Output gains may mask learning changes	Skill development is rarely tracked long term	Longitudinal field study	Skill acquisition and retention	Assisted versus unassisted work	Performance is not expertise	When does augmentation build durable expertise?
Experience heterogeneity	Workers may benefit differently	Short-run workplace evidence	Repeated-measures field study	Experience, task mastery, dependence	Novice and expert roles	Avoid permanent equalization claims	Who learns from AI assistance?
Trust calibration	Reliance can help or harm	Trust measures vary	Behavioral experiments plus field observation	Appropriate acceptance, override, verification	High- and low-consequence tasks	More trust is not always better	When is reliance warranted?
Knowledge diversity	Individual gains may obscure collective loss	Collective consequences remain conditional	Team and network designs	Unique information and convergence	Individual versus team use	Do not scale individual effects automatically	When does common AI advice homogenize knowledge?
Enacted configuration	Formal design may differ from practice	Situated use is underobserved	Process and ethnographic research	Actual authority and exception handling	Organizations using similar systems	Formal permission is not substantive power	How do configurations evolve in use?
Governance	Accountability and integrity remain incompletely tested	Principles exceed causal evidence	Comparative longitudinal designs	Contestability, participation, accountability	HR and non-HR decisions	Safeguard is not proven outcome	Which governance arrangements preserve agency without blocking useful augmentation?

Future research

The framework requires tests that distinguish levels of analysis and temporal processes. A multilevel review of AI in organizations shows that individual, team, and organizational phenomena cannot be treated as interchangeable outcomes of a common technology exposure [32]. Future studies should therefore specify whether agency, expertise, trust, and redesign are measured at the worker, dyad, team, job, or organizational level and identify mechanisms connecting those levels rather than assuming upward or downward transfer.

Research should also replace loose claims of "human–AI complementarity" with explicit comparative benchmarks. Complementarity requires showing when joint human–AI performance exceeds relevant human-only and AI-only alternatives and identifying the informational or capability conditions producing that advantage [33]. The same logic should be extended beyond performance to learning and judgment: a configuration that improves immediate output may still alter expertise accumulation or reliance in ways invisible to short experiments.

Task heterogeneity is another decisive boundary. Field-experimental evidence shows that AI effects can differ sharply depending on whether tasks fall inside or outside the technology's capability frontier [34]. Longitudinal field experiments, natural experiments, repeated skill assessments, and comparative configuration studies are therefore needed to test whether the proposed relationships persist as models, tasks, and worker expertise change. Strong tests should permit disconfirmation, including evidence that configuration categories overlap, agency is unaffected, or predicted feedback relationships fail to emerge.

Measurement should also separate technological capability from legitimate authority. Studies can record whether systems merely recommend, automatically execute, or constrain feasible alternatives, while independently measuring who remains accountable and who can initiate review. This distinction would clarify whether apparent autonomy reflects meaningful influence or only responsibility retained after substantive control has shifted.

Conclusion

Digital augmentation is best understood as a problem of work redesign rather than as a binary choice between human labor and technological substitution. Across heterogeneous evidence, technological systems can redistribute discretion, alter access to developmental work, change patterns of reliance, and reorganize coordination and decision authority. These processes need not move in the same direction: improved immediate performance can coexist with uncertain expertise trajectories, and formal human involvement can coexist with constrained substantive agency.

This integrative review contributes a configuration-sensitive framework connecting task and technology conditions, organizational governance, agency allocation, expertise trajectories, trust calibration, and redesigned work characteristics. Its purpose is analytical rather than prescriptive. The framework does not establish causal pathways, universal superiority of augmentation, or readiness of any configuration for implementation. Its value depends on whether future longitudinal, comparative, experimental, qualitative, and multilevel research can test, refine, or reject its proposed relationships. Work redesign after digital augmentation should therefore be evaluated by how human and technological capabilities are organized in practice, not by the presence of artificial intelligence alone.

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References

1. Parker SK, Grote G. Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. Appl Psychol. 2022;71(4):1171-204. doi:10.1111/apps.12241
2. Raisch S, Krakowski S. Artificial intelligence and management: The automation-augmentation paradox. Acad Manage Rev. 2021;46(1):192-210. doi:10.5465/amr.2018.0072
3. Faraj S, Pachidi S, Sayegh K. Working and organizing in the age of the learning algorithm. Inf Organ. 2018;28(1):62-70. doi:10.1016/j.infoandorg.2018.02.005
4. Kellogg KC, Valentine MA, Christin A. Algorithms at work: The new contested terrain of control. Acad Manage Ann. 2020;14(1):366-410. doi:10.5465/annals.2018.0174
5. Vial G. Understanding digital transformation: A review and a research agenda. J Strateg Inf Syst. 2019;28(2):118-44. doi:10.1016/j.jsis.2019.01.003
6. Snyder H. Literature review as a research methodology: An overview and guidelines. J Bus Res. 2019;104:333-9. doi:10.1016/j.jbusres.2019.07.039
7. Kraus S, Breier M, Lim WM, Dabić M, Kumar S, Kanbach D, et al. Literature reviews as independent studies: Guidelines for academic practice. Rev Manag Sci. 2022;16(8):2577-95. doi:10.1007/s11846-022-00588-8
8. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ. 2021;372. doi:10.1136/bmj.n71
9. Murray A, Rhymer J, Sirmon DG. Humans and technology: Forms of conjoined agency in organizations. Acad Manage Rev. 2021;46(3):552-71. doi:10.5465/amr.2019.0186
10. Curchod C, Patriotta G, Cohen L, Neysen N. Working for an algorithm: Power asymmetries and agency in online work settings. Adm Sci Q. 2020;65(3):644-76. doi:10.1177/0001839219867024
11. Grønsund TR, Aanestad M. Augmenting the algorithm: Emerging human-in-the-loop work configurations. J Strateg Inf Syst. 2020;29(2):101614. doi:10.1016/j.jsis.2020.101614
12. Möhlmann M, Zalmanson L, Henfridsson O, Gregory RW. Algorithmic management of work on online labor platforms: When matching meets control. MIS Q. 2021;45(4):1999-2022. doi:10.25300/MISQ/2021/15333
13. Beane M. Shadow learning: Building robotic surgical skill when approved means fail. Adm Sci Q. 2019;64(1):87-123. doi:10.1177/0001839217751692
14. Noy S, Zhang W. Experimental evidence on the productivity effects of generative artificial intelligence. Science. 2023;381(6654):187-92. doi:10.1126/science.adh2586
15. Brynjolfsson E, Li D, Raymond LR. Generative AI at work. Q J Econ. 2025;140(2):889-942. doi:10.1093/qje/qjae044
16. Lebovitz S, Lifshitz-Assaf H, Levina N. To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. Organ Sci. 2022;33(1):126-48. doi:10.1287/orsc.2021.1549
17. Glikson E, Woolley AW. Human trust in artificial intelligence: Review of empirical research. Acad Manage Ann. 2020;14(2):627-60. doi:10.5465/annals.2018.0057
18. Logg JM, Minson JA, Moore DA. Algorithm appreciation: People prefer algorithmic to human judgment. Organ Behav Hum Decis Process. 2019;151:90-103. doi:10.1016/j.obhdp.2018.12.005
19. Fügener A, Grahl J, Gupta A, Ketter W. Will humans-in-the-loop become Borgs? Merits and pitfalls of working with AI. MIS Q. 2021;45(3):1527-56. doi:10.25300/MISQ/2021/16553
20. Gaube S, Suresh H, Raue M, Merritt A, Berkowitz SJ, Lermer E, et al. Do as AI say: Susceptibility in deployment of clinical decision-aids. NPJ Digit Med. 2021;4(1):31. doi:10.1038/s41746-021-00385-9

21. Parent-Rocheleau X, Parker SK. Algorithms as work designers: How algorithmic management influences the design of jobs. Hum Resour Manag Rev. 2022;32(3):100838. doi:10.1016/j.hrmr.2021.100838
22. Jarrahi MH. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Bus Horiz. 2018;61(4):577-86. doi:10.1016/j.bushor.2018.03.007
23. Shrestha YR, Ben-Menahem SM, von Krogh G. Organizational decision-making structures in the age of artificial intelligence. Calif Manage Rev. 2019;61(4):66-83. doi:10.1177/0008125619862257
24. Seeber I, Bittner E, Briggs RO, de Vreede T, de Vreede GJ, Elkins A, et al. Machines as teammates: A research agenda on AI in team collaboration. Inf Manag. 2020;57(2):103174. doi:10.1016/j.im.2019.103174
25. Bailey DE, Barley SR. Beyond design and use: How scholars should study intelligent technologies. Inf Organ. 2020;30(2):100286. doi:10.1016/j.infoandorg.2019.100286
26. Makarius EE, Mukherjee D, Fox JD, Fox AK. Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. J Bus Res. 2020;120:262-73. doi:10.1016/j.jbusres.2020.07.045
27. Bailey DE, Faraj S, Hinds PJ, Leonardi PM, von Krogh G. We are all theorists of technology now: A relational perspective on emerging technology and organizing. Organ Sci. 2022;33(1):1-18. doi:10.1287/orsc.2021.1562
28. Langer M, Landers RN. The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. Comput Human Behav. 2021;123:106878. doi:10.1016/j.chb.2021.106878
29. Tambe P, Cappelli P, Yakubovich V. Artificial intelligence in human resources management: Challenges and a path forward. Calif Manage Rev. 2019;61(4):15-42. doi:10.1177/0008125619867910
30. Leicht-Deobald U, Busch T, Schank C, Weibel A, Schafheitle S, Wildhaber I, et al. The challenges of algorithm-based HR decision-making for personal integrity. J Bus Ethics. 2019;160(2):377-92. doi:10.1007/s10551-019-04204-w
31. Rodgers W, Murray JM, Stefanidis A, Degbey WY, Tarba SY. An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. Hum Resour Manag Rev. 2023;33(1):100925. doi:10.1016/j.hrmr.2022.100925
32. Bankins S, Ocampo AC, Marrone M, Restubog SLD, Woo SE. A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. J Organ Behav. 2024;45(2):159-82. doi:10.1002/job.2735
33. Hemmer P, Schemmer M, Kühl N, Vössing M, Satzger G. Complementarity in human-AI collaboration: Concept, sources, and evidence. Eur J Inf Syst. 2025;34(6):979-1002. doi:10.1080/0960085X.2025.2475962
34. Dell'Acqua F, McFowland E III, Mollick E, Lifshitz H, Kellogg KC, Rajendran S, et al. Navigating the jagged technological frontier: Field experimental evidence of the effects of artificial intelligence on knowledge worker productivity and quality. Organ Sci. 2026;37(2):403-23. doi:10.1287/orsc.2025.21838