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The Absorptive Bypass: How Generative AI Decouples Organizational Action from Knowledge Assimilation

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Abstract: Generative artificial intelligence (GenAI) can convert a prompt into an actionable prescription before an organizational work system has acquired the task knowledge needed to evaluate or adapt it. Existing research explains AI augmentation, substitution, knowledge depreciation, and new modes of organizational learning, but it does not isolate how successful AI-mediated action can recursively reinforce nonlearning. This conceptual article develops absorptive bypass, a recurrent AI-enabled work process in which actionable prescriptions are enacted and routinized while acquisition, validation, and retention of task knowledge are materially abbreviated or omitted. Integrating absorptive-capacity theory, organizational learning and memory, and technology-affordance research, the article distinguishes an assimilative pathway from a bypass pathway and advances four propositions. Direct-use affordance increases bypass episodes, especially when prior expertise and accountability are limited. Favorable but low-diagnosticity feedback reinforces recurrence. Greater cumulative bypass intensity reduces distributed epistemic coverage and produces adaptive fragility that becomes visible under task novelty, model change, loss of access, or demands for independent justification. Actualized human-validated knowledge-integration routines interrupt and redirect the process. The model distinguishes bypass from efficient dependence on governed AI as organizational memory and specifies boundary conditions under which reliance remains legitimate. It contributes a process explanation for why immediate performance and durable capability can diverge and offers testable indicators based on independent explanation, modification, transfer, and recovery capacity.

Keywords: Generative Artificial Intelligence, Absorptive Capacity, Organizational Learning, Organizational Memory, Adaptive Fragility

Introduction

Generative artificial intelligence (GenAI) compresses the distance between a question and an executable organizational response. A manager can obtain a pricing recommendation, a service team can generate a workflow, or an analyst can produce a risk narrative without reproducing the search, comparison, and interpretation behind the output. Field evidence indicates that GenAI can improve the productivity and quality of knowledge work, although gains depend on task conditions and the technology's competence frontier (Dell'Acqua et al., 2026). Contemporary management research accordingly treats AI as a source of automation, augmentation, hybrid problem solving, and reconfigured decision work rather than as a single-purpose tool (Hillebrand et al., 2025; Raisch & Fomina, 2025; Raisch & Krakowski, 2021; Schulte & Kanbach, 2026). Yet a performance-centered account leaves a consequential possibility underdeveloped: an organization may act successfully while learning too little to evaluate, modify, or defend the action when conditions change.

Organizational action and organizational knowledge accumulation are not equivalent. Absorptive capacity concerns the recognition, assimilation, transformation, and use of external knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002). Organizational learning and

memory research likewise locates retained knowledge in people, routines, structures, and records, not merely in an observed outcome (Levitt & March, 1988; Walsh & Ungson, 1991). GenAI unsettles the usual sequence because its outputs can arrive as plans, classifications, explanations, or scripts that are ready for enactment. The organization can therefore obtain application-like behavior without first building the distributed knowledge ordinarily presumed to support application.

Recent research identifies important neighboring phenomena, and a systematic review maps the expanding literature on GenAI and organizational learning (Lenart, 2026). Pletsch et al. (2026) describe dimensional asymmetries in GenAI-enabled knowledge management. Wiesenfeld and Kellogg (2026) explain how large language models create new affordances for organizational search, creation, transfer, and forgetting. Gerlach and Lange (2026) theorize machine-learning-driven knowledge depreciation. Devigili et al. (2026) identify early changes in job-posting demand for selected organizing skills after GenAI exposure, while Reif and Cummings (2026) examine how substitution can weaken knowledge-intensive teams. These works show that AI changes knowledge and skill systems. They do not isolate the recursive chain in which direct-use affordance enables abbreviated assimilation, favorable but low-diagnosticity feedback legitimizes recurrence, and greater cumulative bypass intensity creates fragility that becomes visible only under perturbation.

This article asks: How and under what conditions does GenAI enable organizational action without corresponding knowledge assimilation, and when does that pathway create adaptive fragility? It introduces absorptive bypass to connect AI-generated prescriptions, outcome feedback, recurrent work practices, and distributed capability. The theory distinguishes applying organizationally accessible knowledge from enacting an epistemically external prescription, specifies why successful outcomes may be weak evidence of learning, and identifies routines that interrupt the bypass pathway.

Research Problem and Purpose

The focal problem is not simply that GenAI can be wrong, opaque, or over trusted. Those conditions can generate immediate decision failure. Absorptive bypass addresses a harder case: the output is useful enough, often enough, that organizational members repeatedly omit reconstruction and validation of the task logic. A prescription may be locally successful while the work system becomes less able to explain why it worked, identify its boundary conditions, or revise it after a distribution shift. Because natural-language explanations can appear coherent without being faithful to the generating process, asking a model to explain its own output does not by itself close this knowledge gap (Parcalabescu & Frank, 2024). Outcome success can therefore mask capability loss.

The unit of analysis is an organizational work system, such as a team, function, or recurring cross-functional process. Knowledge need not reside in every member. It may be distributed across specialists, routines, governed technical systems, and validated records. A prescription is epistemically external to the focal work system when its evidentiary and causal basis is neither accessible nor retained in that system, regardless of whether the organization owns the model. This definition prevents legal ownership, local hosting, or data custody from being mistaken for task knowledge. Direct-use affordance, prior task knowledge, and decision accountability operate at the actor-task encounter; bypass episodes are enacted within the focal work system; and recurrence, distributed epistemic coverage, and adaptive fragility are evaluated at the work-system level.

The article's purpose is theory building, not empirical estimation. It defines the process, distinguishes it from automation, deskilling, opacity, and ordinary outsourcing, and derives four propositions suitable for later testing. The intended contribution is diagnostic: to explain why short-run output quality and long-run adaptive capability may move in opposite directions even when no visible AI failure has occurred.

Conceptual Method

The article uses a problem-driven conceptual synthesis. The synthesis was assembled through targeted searches of publisher indexes and DOI-linked records, supplemented by backward and forward citation tracing from key 2024–2026 articles. Search combinations joined "generative AI" or "artificial intelligence" with "organizational learning," "knowledge management," "absorptive capacity," "skill depreciation," "human-AI teams," "feedback," and "validation." The search closed in August 2026. Priority was given to peer-reviewed work published from 2024 through 2026, then to relevant work from 2022 onward; older sources were retained only when they established indispensable constructs. Review-method guidance informed the alignment among the motivating problem, theoretical foundations, and proposed contribution (Kunisch et al., 2023; Lim, 2026).

The search was targeted and iterative, not a systematic review, so the reference set is not treated as an exhaustive dataset. Four literatures were selected for distinct explanatory roles: absorptive capacity defines acquisition and assimilation; organizational learning and memory locate distributed retention; contemporary AI research explains augmentation, substitution, hybrid teams, and changing skill demands; and affordance research explains how situated technology use makes direct enactment possible. Disconfirming work that treats AI as a component of organizational memory or capability was deliberately included to define when dependence is legitimate rather than bypass. The resulting claims concern conceptual relationships and boundary conditions, not prevalence or effect size.

Theoretical Foundations

Absorptive capacity is the ability to recognize the value of external knowledge, assimilate it, and apply it (Cohen & Levinthal, 1990). The distinction between potential and realized absorptive capacity further separates acquisition and assimilation from transformation and exploitation (Zahra & George, 2002). Recent knowledge-management research shows that GenAI can support acquisition, sharing, application, and transformation unevenly, creating an application-versus-assimilation asymmetry rather than uniformly strengthening every dimension (Alavi et al., 2024; Pletsch et al., 2026). The present theory focuses on the pathway outside the canonical acquisition-assimilation-transformation/application logic: a prescription can guide action before its task logic becomes accessible organizational knowledge.

This pathway requires a distinction between knowledge application and prescription enactment. Application denotes action supported by task knowledge available within the focal work system. Enactment denotes action guided by an output even when the system cannot independently reconstruct, test, or modify its basis. Labeling every successful enactment as exploitation would make absorptive capacity circular because the action itself would become proof that the underlying knowledge was absorbed. The distinction instead asks what evaluative and adaptive capacity remains after the action.

Organizational learning and memory explain the temporal consequence. Experience can be encoded into routines even when actors draw incorrect causal inferences, and stable performance does not show that double-loop learning has occurred (Levitt & March, 1988; Auqui-Caceres & Furlan, 2023). Organizational memory may reside in people, structures, routines, or external archives (Walsh & Ungson, 1991). GenAI can become part of that memory architecture by supporting retrieval, combination, and transfer (Storey, 2025; Wiesenfeld & Kellogg, 2026). The question is therefore not whether knowledge is stored "inside" a human. It is whether the work system has governed access to sufficiently validated knowledge to detect drift, contest assumptions, and recover.

Research on hybrid teams reinforces this distributed view. Intelligent agents can participate in a group mind when responsibilities, expertise locations, and retrieval relations are understood and reliable (Hopf et al., 2025). Human and artificial intelligence may also form complementary problem-solving systems when actors allocate tasks according to relative

strengths and preserve coordination (Raisch & Fomina, 2025). Dependence on an AI system is thus legitimate rather than bypass when the knowledge arrangement is governed, versioned, auditable, independently validated, replaceable, and supported by failover capacity. Bypass arises when repeated action depends on nonretained or insufficiently validated prescriptions and the system lacks distributed capacity to recognize and repair failure.

Affordance theory explains why the sequence can change. A technological affordance is a situated possibility for action arising from the relation between artifact features and actor goals, rather than a deterministic property of the technology (Leonardi, 2011). GenAI's conversational interface, rapid response, and ability to produce near-finished artifacts create direct-use affordance: the possibility of treating an output as ready for enactment with little intervening inquiry. Observed side effects of ChatGPT-enabled work similarly depend on how actors actualize its affordances within local practices (Retkowsky et al., 2024). Expertise, accountability, time pressure, and workflow design therefore determine whether direct use becomes bypass.

Taken together, these foundations locate the paper's novelty narrowly. Pletsch et al. (2026) identify uneven effects across knowledge-management dimensions; Wiesenfeld and Kellogg (2026) theorize an abundance of generative learning and forgetting; Gerlach and Lange (2026) explain knowledge depreciation; Devigili et al. (2026) identify early demand-side skill reprioritization; and Reif and Cummings (2026) explain team-level substitution risks. Absorptive bypass contributes the recursive process that links a direct-use affordance to favorable low-diagnosticity feedback, recurrent abbreviated assimilation, reduced distributed epistemic coverage, and perturbation-revealed adaptive fragility.

The Absorptive-Bypass Model

Absorptive bypass is a recurrent AI-enabled work process in which actionable prescriptions are enacted and routinized while acquisition, validation, and retention of task knowledge are materially abbreviated or omitted. An action prescription is an AI output expressed with enough specificity to guide a consequential choice or behavior. A bypass episode occurs when a focal work system enacts such a prescription while materially abbreviating or omitting those knowledge processes. Recurrent episodes constitute the process; adaptive fragility is a possible downstream consequence rather than part of the definition. Table 1 organizes the seven constructs by working definition and boundary or indicator; the third column guides readers in distinguishing the proposed process from adjacent phenomena.

Table 1. Constructs, Definitions, and Boundaries

Construct	Working definition	Boundary or indicator
Absorptive bypass	Recurrent AI-enabled work process in which actionable prescriptions are enacted and routinized while acquisition, validation, and retention of task knowledge are materially abbreviated or omitted.	A recurrent process. A bypass episode is one enactment in which acquisition, validation, or retention is materially abbreviated or omitted; reliance alone is not bypass.
Direct-use affordance	Situated possibility of enacting an AI output with little inquiry between generation and action.	An affordance rather than actual use; depends on output form, expertise, accountability, pressure, and workflow.
Task knowledge	Knowledge sufficient to evaluate evidence, assumptions, limits, and modifications for the focal recurring task.	May be distributed across people, routines, governed systems, and validated records.
Distributed epistemic coverage	Extent to which the focal work system can independently identify relevant evidence, test assumptions, modify action, and recover without relying on the originating prescription.	A work-system-level mediator; no single member must hold all knowledge, but sufficient independent challenge and recovery capacity must remain.

Construct	Working definition	Boundary or indicator
Feedback diagnosticity	Extent to which outcome feedback discriminates among causal explanations, reveals boundary conditions, and supports revision of assumptions.	Independent of favorability; favorable or unfavorable outcomes may be weakly diagnostic.
Adaptive fragility	Latent inability to evaluate, revise, justify, transfer, or recover when familiar conditions no longer hold.	A predicted consequence revealed by perturbation, not part of the bypass definition.
Actualized human-validated knowledge-integration routines	Actualized practices that independently test, contest, retain, and update knowledge associated with AI prescriptions.	Formal policy alone is insufficient; evidence must extend beyond the originating prescription or model.

Building on these distinctions, Figure 1 maps the model's constructs across two contrasting pathways. Read each pathway from top to bottom. The left pathway shows how independent inquiry, validation, and diagnostic feedback support retained task knowledge and adaptive capacity. The right pathway shows how direct-use affordance can initiate a bypass episode, how favorable but low-diagnosticity feedback reinforces recurrence, and how cumulative bypass reduces distributed epistemic coverage until perturbation reveals adaptive fragility. The dashed path represents the proposed moderating effect of actualized human-validated knowledge-integration routines on the direct-use-to-bypass relationship, while the curved arrow shows how those routines can redirect prescriptions toward inquiry and validation.

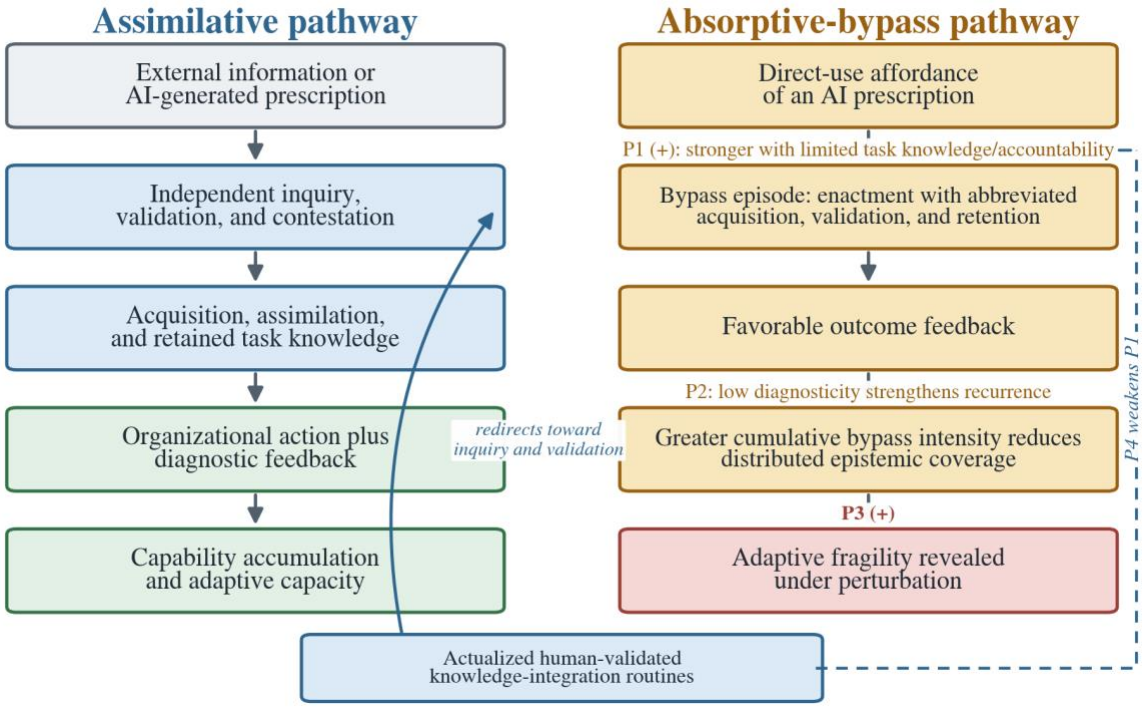

Figure 1. Assimilative and Absorptive-Bypass Pathways in GenAI-Enabled Organizational Action. *Source:* Authors' original contribution.

Propositions and Discussion

Direct-use affordance lowers the cost and visibility of intermediate inquiry. When an AI output is formatted as a decision, plan, or script, validation becomes a separate activity that consumes time without necessarily changing the immediate deliverable. Under deadline pressure, limited accountability, or weak domain expertise, actors can rationally omit that activity. The output then substitutes not only for execution effort but also for opportunities to acquire and integrate task knowledge. This mechanism can operate even when a person

remains visibly in the loop, because formal human presence does not establish meaningful evaluative capacity (Hillebrand et al., 2025; Retkowsky et al., 2024).

The predicted relationship has important boundaries. Direct use is not bypass when knowledgeable actors already possess enough task knowledge to validate and modify the prescription. High personal accountability, strong professional norms, and output designs that present alternatives or uncertainty may also trigger inquiry. Conversely, workflow-ready prescriptions should be more likely to produce bypass episodes when prior task knowledge is limited, accountability is diffuse, and the task's causal structure is difficult to observe. The proposition therefore concerns the probability of an episode, not inevitable dependence on GenAI.

Proposition 1. The stronger the direct-use affordance of GenAI within a recurring organizational task, the greater the likelihood of a bypass episode, particularly when prior task knowledge and decision accountability are limited.

A bypass episode becomes recurrent when actors and routines treat it as a successful way of working. Outcome favorability can supply that reinforcement, but favorability does not show why the action worked. Feedback diagnosticity captures the difference. Highly diagnostic feedback discriminates among causal explanations, reveals boundary conditions, and supports revision of assumptions. Low-diagnosticity feedback reports that a target was reached while leaving competing explanations unresolved. A sales increase after an AI-generated campaign, for example, may coincide with seasonality or a competitor's withdrawal. The result is favorable but weak evidence about the prescription's causal validity.

The object being reinforced is the direct-use routine: obtain a prescription, enact it with abbreviated inquiry, and repeat. Favorable outcomes can legitimate algorithmic decisions even when process quality remains uncertain (Martin & Waldman, 2023). Organizational learning research also cautions that actors encode inferences from experience and may reproduce success routines without revising the governing assumptions behind them (Levitt & March, 1988; Auqui-Caceres & Furlan, 2023). When feedback is highly diagnostic, favorable outcomes can instead contribute to assimilation because actors learn which mechanisms and conditions mattered. Unfavorable outcomes may trigger search. Favorability and diagnosticity must therefore remain analytically separate.

Proposition 2. Favorable outcome feedback will more strongly reinforce recurrence of the direct-use routine after a bypass episode when feedback diagnosticity is low than when feedback diagnosticity is high.

Cumulative bypass intensity is the proportion of recurring task episodes enacted through bypass over a specified period. Greater cumulative bypass intensity alters the composition of capability. The work system may accumulate prompt conventions, access routines, and confidence in obtaining usable outputs while receiving fewer opportunities to build independent task knowledge. Distributed epistemic coverage narrows when fewer people, routines, or records can identify relevant evidence, test assumptions, or modify the action without the originating prescription. This loss can remain latent while the model remains available and tasks resemble familiar cases.

Perturbation reveals the consequence. Task novelty, model updates, access loss, vendor discontinuity, model drift, or demands for defensible justification can make prior direct-use routines insufficient. Adaptive fragility is therefore not current poor performance and not a synonym for opacity. Adaptive fragility is a task-specific epistemic vulnerability within a focal work system, not an assessment of the organization's general resilience or broader capacity to reconfigure resources. It is narrower than general deskilling because skills may remain elsewhere, and it differs from ordinary outsourcing because a firm can outsource execution while retaining specifications, validation expertise, supplier challenge, and replacement

capacity. The decisive mechanism is reduced opportunity for independent task-knowledge accumulation within the focal system.

The argument aligns with evidence that machine substitution changes the experiences from which organizations learn (Balasubramanian et al., 2022), that machine learning can contribute to knowledge depreciation (Gerlach & Lange, 2026), and that GenAI exposure can shift demand for selected organizing skills (Devigili et al., 2026). It also extends the team-level dilemma identified by Reif and Cummings (2026). GenAI can produce a plausible retrospective explanation, but explanation fluency is not equivalent to faithfulness or independent validation (Parcalabescu & Frank, 2024). Repetition therefore matters because it removes occasions for accumulating the knowledge needed at the moment of perturbation.

Proposition 3. Within a recurring organizational task, greater cumulative bypass intensity will increase adaptive fragility by reducing distributed epistemic coverage, with the effect becoming observable under task novelty, model change, model unavailability, or demands for independent justification.

Actualized human-validated knowledge-integration routines can interrupt the process. These routines require the work system to articulate, independently test, contest, retain, and update the evidence, assumptions, alternatives, and boundary conditions associated with consequential prescriptions. Examples include pre-action challenge reviews, comparison with external evidence, counterfactual checks, independent replication, limited sandbox trials, assumption logs, and after-action reviews that compare predicted mechanisms with observed results. Sandbox experiments and structured exploration can make organizational learning from GenAI more deliberate (Te'eni et al., 2026), while trust-calibration routines can specify when teams should override AI recommendations (Atanassova et al., 2026).

Two boundaries are essential. First, formal policy is not the moderator; actualized practice is. A review requirement that routinely receives a rubber stamp does not integrate knowledge. Second, validation must rely on evidence or expertise outside the originating prescription. Asking the same model to explain or verify itself may add text without adding independent epistemic coverage. Effective routines assign domain expertise, challenge and stop authority, retention responsibility, and subsequent testing. Structural feedback channels can help preserve and update what frontline actors learn across organizational levels (Hart, 2025b).

These routines need not eliminate efficiency gains. The model suggests allocating validation effort according to consequence, irreversibility, novelty, uncertainty, and feedback diagnosticity. Low-consequence and readily reversible tasks may warrant little retained expertise. High-consequence recurring work requires stronger independent coverage. The moderator should therefore weaken the translation of direct-use affordance into bypass by redirecting selected prescriptions into inquiry and retention.

Proposition 4. Actualized human-validated knowledge-integration routines will weaken the positive relationship between direct-use affordance and bypass episodes.

Theoretical Contributions

The model makes three contributions. First, it identifies a pathway outside the canonical acquisition-assimilation-transformation/application logic of absorptive capacity. GenAI permits action to occur before acquisition and assimilation, so application-like behavior cannot be treated as evidence of realized capacity. The process definition avoids circularity by separating recurrent abbreviated knowledge work from its predicted consequence, adaptive fragility.

Second, the model explains success-driven organizational nonlearning. Prominent AI-risk accounts foreground error, opacity, rejection, or substitution. Absorptive bypass predicts that vulnerability can also grow because outputs work. Favorable low-diagnosticity feedback

reinforces a direct-use routine without revealing whether causal knowledge accumulated. The recursive chain clarifies how local success can coexist with progressive reductions in distributed epistemic coverage.

Third, the model distinguishes inefficient nonlearning from legitimate dependence on AI as organizational memory. Governed, versioned, auditable, validated, replaceable systems with understood expertise locations and failover capacity can extend organizational capability. Bypass instead describes recurrent enactment when the evidentiary basis is inaccessible or unretained and independent challenge or recovery capacity is insufficient. This boundary makes the theory falsifiable and prevents reliance itself from being coded as dysfunction.

Relative to adjacent accounts, knowledge depreciation captures declining value of existing knowledge; team substitution concerns redistribution of work; generative organizational learning encompasses search, creation, transfer, and forgetting; and GenAI can be embedded in organizational memory (Gerlach & Lange, 2026; Reif & Cummings, 2026; Storey, 2025; Wiesenfeld & Kellogg, 2026). Absorptive bypass instead isolates recurrent enactment before task knowledge becomes accessible to the focal work system. It explains how capability loss may be reinforced by successful performance without assuming error, explicit replacement, or that reliance itself is dysfunctional.

Practical Implications

The model suggests that managers complement output metrics with capability-retention indicators. Accuracy, time saved, and adoption rates assess current production, not whether the work system can challenge the prescription later. Organizations could periodically test whether relevant members can explain evidence and assumptions without model assistance, modify a prescription under altered constraints, transfer its logic to an adjacent task, and recover during a model or vendor outage. These are proposed diagnostics rather than empirically validated performance measures.

A workable governance sequence begins with recurring tasks rather than technologies. Managers can identify tasks in which GenAI outputs can be enacted directly and classify them by consequence, reversibility, novelty, and feedback diagnosticity. For higher-risk tasks, the work system should assign a validation owner and independent challenge authority, retain the evidentiary rationale and boundary conditions, and periodically test performance under altered constraints or temporary model unavailability. These controls operationalize trust calibration and deliberate organizational learning without requiring human duplication of every AI-supported activity (Atanassova et al., 2026; Hillebrand et al., 2025; Te'eni et al., 2026). Governance should then monitor cumulative bypass intensity alongside distributed epistemic coverage. A rising proportion of bypass episodes is not automatically dysfunctional, but it should trigger review when fewer people, routines, or records can independently explain, modify, transfer, or recover the task. Structural feedback channels can connect those findings to workflow redesign, training, version control, and escalation decisions (Hart, 2025b). The resulting control intensity should vary with the cost and recoverability of failure.

Implementation could also distinguish artifact storage from knowledge integration. Saving prompts and outputs preserves records but does not establish that their assumptions were tested or can be revised. The model suggests assigning ownership for validation, challenge authority, rationale retention, version control, and failover. Healthcare-retail implementation work illustrates how leadership, workforce adaptation, and workflow design shape the organizational consequences of AI adoption (Hart, 2025a). The objective is not maximal human duplication of AI work, but sufficient distributed knowledge to evaluate, adapt, and recover where the cost of failure warrants it.

Limitations and Future Research

The model applies to recurring organizational work in which GenAI produces actionable prescriptions and task knowledge could, in principle, be integrated. It does not imply that every AI use should build durable human expertise. Deliberate dependence may be efficient for one-off, low-consequence, reversible, or highly standardized tasks, particularly when validation costs exceed plausible losses. AI can also serve as legitimate organizational memory when access, versioning, auditability, external validation, replacement, and failover are robust. The boundary may shift as vendors, models, and interfaces change, so continuity and model-drift risk require separate attention.

The targeted conceptual synthesis cannot estimate prevalence, causal magnitude, or sector differences. Future research can test the propositions with longitudinal field studies, process tracing, and repeated-task experiments. A strong design would vary direct-use affordance and feedback diagnosticity, estimate cumulative bypass intensity by recording bypass episodes relative to total recurring-task opportunities, and then introduce task novelty, model change, or temporary unavailability. Outcomes could include independent explanation accuracy, constraint-sensitive modification, transfer, recovery time, and the distribution of validated knowledge across the work system. Matched-unit studies could compare actualized challenge routines while accounting for prior expertise, task consequence, validation cost, vendor continuity, and model drift. Research should also test when external assurance can substitute for internal assimilation and when dependence outperforms capability retention.

Measurement must preserve construct boundaries. Cumulative bypass intensity should be calculated as bypass episodes divided by total recurring-task opportunities, not inferred from general AI-use frequency. Distributed epistemic coverage should be assessed at the work-system level through independent explanation, challenge, modification, transfer, and recovery capacity, not one employee's self-reported expertise. Adaptive fragility should be measured only when a perturbation creates a demand for those capacities; routine output quality is not a valid proxy. Studies should also separate feedback favorability from diagnosticity and code human review as a knowledge-integration routine only when it draws on evidence or expertise independent of the originating prescription. These distinctions would support discriminant-validity tests and prevent overlapping measures from reproducing the propositions by definition.

Conclusions

GenAI allows organizations to obtain executable prescriptions without reproducing the knowledge work that makes those prescriptions independently evaluable. Absorptive bypass explains how direct-use affordance initiates episodes of abbreviated assimilation, how favorable low-diagnosticity outcomes reinforce a recurring routine, and how greater cumulative bypass intensity can reduce distributed epistemic coverage until perturbation reveals adaptive fragility. Actualized human-validated knowledge-integration routines can interrupt and redirect the pathway. The central lesson is precise: evidence that an AI-mediated action worked is not, by itself, evidence that the organization learned, but dependence remains legitimate when validated knowledge, challenge authority, auditability, and recovery capacity are deliberately preserved.

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