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From Organizational AI Capability to Employee Enactment in Public Sector Organizations

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Abstract

Artificial intelligence capability is increasingly viewed as an important organizational resource in public-sector digital transformation, yet the possession of AI-related resources does not necessarily translate into sustained employee-level use and performance. This article develops an accountability-bounded enactment framework explaining how organizational AI capability becomes consequential through employee adaptation and work practices. Using a theory-synthesis approach supported by structured thematic and targeted literature searches, the study integrates research on AI capability, organizational learning, employee unlearning, technology enactment, AI use, sustainable employee performance, and public-sector accountability. The framework generates three main theoretical insights. First, employee learning and unlearning are not treated merely as parallel adaptive mechanisms: employee unlearning is also proposed to condition whether newly developed AI competence becomes task-integrated use. Second, where sanctioned learning opportunities remain available, procedural rigidity is expected to constrain capability-driven unlearning more strongly than capability-driven learning. Third, accountability clarity strengthens the positive relationship between task-integrated AI use and employee sustainable performance, while not eliminating other potential costs of AI use such as cognitive burden, dependence, or technostress. These relationships are theoretically derived rather than empirically tested. The framework contributes a cross-level explanation of AI capability enactment in public-sector organizations by showing how competence development, routine revision, task-integrated AI use, and accountability conditions jointly shape whether organizational AI capability produces sustainable employee outcomes.

KEYWORDS

organizational ai capability; employee ai learning; employee unlearning; technology enactment; sustainable performance.

Introduction

Artificial intelligence has become increasingly embedded in public-sector digital transformation, supporting administrative work, decision-making, service delivery, and policy implementation (Chen et al., 2023; Haesevoets et al., 2025; Kulal et al., 2024). Yet expanding AI-related resources and capabilities does not necessarily produce corresponding changes in how employees perform their daily work. Public organizations may acquire AI systems, develop data resources, and strengthen AI-related managerial capabilities while employees continue to rely on established routines or use AI only marginally (Hansen et al., 2024; Mikalef & Gupta, 2021). The theoretical problem is therefore not simply whether public organizations possess AI capability, but how that capability becomes translated into employee-level adaptation and actual work practices.

Organizational AI capability provides an important starting point. Mikalef and Gupta (2021) conceptualize AI capability as an organizational capacity to mobilize and orchestrate AI-specific resources to achieve organizational objectives. Subsequent research has linked AI capability to organizational performance and public value creation (Mikalef et al., 2022, 2023; van Noordt & Tangi, 2023), while related studies indicate that organizational digital and AI capabilities can also affect employee-level outcomes

through learning and other individual mechanisms (Bibi et al., 2025; Fu et al., 2023). However, the cross-level mechanisms through which organizational AI capability becomes embedded in employees' everyday work remain less explicit.

This gap is especially important because meaningful AI use can require more than access or willingness to adopt technology. Predictive and generative AI applications differ in their technical properties, but many require employees to interpret outputs whose relevance, reliability, or appropriate role cannot be determined solely by operating the technology (Holmström & Carroll, 2025; Leyer & Schneider, 2021). Employees may need to develop task-relevant competence, determine when verification is required, and integrate AI-generated information with professional judgment. Technology acceptance alone therefore does not fully explain whether AI becomes substantively incorporated into work.

Learning alone is also insufficient. Employees may acquire AI-related knowledge while continuing to follow routines developed before AI was introduced. Research on unlearning suggests that adaptation can require conscious revision or relinquishment of established assumptions and routines that no longer fit changed technological conditions (Koddebusch et al., 2024; Visser, 2017; Wang et al., 2025). Employee AI learning and employee unlearning therefore perform different adaptive functions: learning develops competence for AI-enabled work, whereas unlearning reduces reliance on path-dependent routines that may prevent that competence from being enacted.

Public-sector organizations make this distinction particularly consequential. Public employees operate within institutional environments shaped by legality, procedural requirements, auditability, and public accountability (Busuioac, 2021; Young et al., 2019; Yuan & Chen, 2025). Some established routines may persist through habit, legacy systems, or duplicated work processes, while others preserve legitimate documentation, due-process, fairness, or accountability functions. Consequently, employees may be able to acquire new AI competence without altering existing procedures, whereas revising routines may expose them to greater uncertainty regarding authorization and responsibility.

Technology enactment provides the conceptual bridge between organizational capability and employee practice. Enactment perspectives emphasize that technologies become organizationally consequential through situated interpretation and use rather than through formal availability alone (Fountain, 2001; Orlikowski, 2000). Building on this logic, the present framework positions organizational AI capability as the organizational resource base, employee AI learning and employee unlearning as complementary adaptive mechanisms, AI use as behavioral enactment, and employee sustainable performance as the downstream employee outcome (De Vos et al., 2020; Ji et al., 2021).

The theoretical perspectives used in the framework perform distinct functions. The Resource-Based View explains why AI-related resources can constitute a strategically valuable organizational base (Barney, 1991), while Dynamic Capabilities Theory explains the need to reconfigure resources and routines under technological change (Teece et al., 1997). Organizational Learning Theory supports the acquisition and revision of knowledge underlying adaptation (Argyris & Schön, 1978), while Social Cognitive Theory helps explain how environmental support and perceived capability facilitate engagement with AI-enabled tasks (Bandura, 1986). Technology enactment connects these organizational and individual processes by explaining how technology becomes consequential through situated work practice.

The contribution of this article is incremental but specific. Fu et al. (2023) provide the closest capability-to-employee comparison: perceived enterprise digital capability is linked to

employee sustainable performance through parallel employee learning and unlearning pathways, with communication feedback moderating the capability-to-learning and capability-to-unlearning relationships. Bibi et al. (2025) similarly connect AI capabilities to an employee-level outcome through cybernetic thinking, with organizational ambidexterity as a moderator, in a private-sector healthcare context. Koddebusch et al. (2024) bring an unlearning lens to digital-government competences, whereas Wang et al. (2025) position individual unlearning as an antecedent of changed technology-use patterns after adoption of intelligent personal assistants. These studies establish important capability-to-employee and unlearning mechanisms, but they do not explain the same public-sector enactment problem addressed here: how organizational AI capability becomes translated into task-integrated AI use under procedural and accountability constraints.

The theoretical advance therefore does not rest on combining learning and unlearning alone. Relative to Fu et al.'s (2023) parallel mediation logic, the present framework additionally theorizes employee unlearning as a conditioning mechanism that strengthens the translation of employee AI learning into task-integrated AI use. It further predicts that procedural rigidity constrains the organizational AI capability–employee unlearning relationship more strongly than the corresponding learning relationship, and that accountability clarity strengthens the AI use–employee sustainable performance relationship. Together, these predictions explain why organizational AI capability may generate employee competence without producing corresponding changes in work routines, substantive AI use, or sustainable performance.

Accordingly, this article addresses two conceptual questions: (1) Through what employee-level mechanisms does organizational AI capability become translated into AI use and employee sustainable performance? and (2) How do procedural rigidity, employee unlearning, and accountability clarity condition this enactment process in public-sector organizations? By answering these questions through theory synthesis, the article develops an accountability-bounded framework of organizational AI capability enactment and derives propositions for subsequent empirical testing.

AI Capability as an Enacted Organizational Capability

Organizational artificial intelligence capability refers to an organization's capacity to purposefully orchestrate AI-related technological, data, human, managerial, and governance resources for organizational tasks and objectives. Following Mikalef and Gupta (2021), the construct is distinguished from the underlying resources themselves: AI systems, data infrastructure, employee expertise, managerial support, and governance arrangements are resource inputs, whereas organizational AI capability concerns the coordinated capacity to mobilize and deploy them.

This distinction is important because possession of AI-related resources does not by itself constitute organizational capability. Resource-Based View logic explains why heterogeneous and strategically relevant AI-related resources may provide a valuable organizational base (Barney, 1991), while Dynamic Capabilities Theory emphasizes the need to reconfigure such resources as technologies, tasks, and environments change (Teece et al., 1997). However, neither perspective alone specifies how organizational capability becomes reflected in employee work behavior.

Technology enactment provides that bridge. Technologies become consequential through the ways employees interpret, appropriate, and incorporate them into situated work practices (Fountain, 2001; Orlikowski, 2000). The present framework therefore treats organizational AI capability as an organizational-level antecedent whose effects depend on employee-level enactment through learning, unlearning, and task-integrated AI use.

This cross-level translation is especially relevant in AI-enabled work because many AI applications increase interpretive demands on employees. Their usefulness can depend on model quality, contextual fit, user input, and subsequent human judgment (Holmström & Carroll, 2025; Leyer & Schneider, 2021). Organizational AI capability becomes behaviorally consequential when employees encounter its resources through work tasks, learning opportunities, managerial guidance, workflow design, and authorized forms of use.

Organizational AI capability nevertheless remains an organizational-level construct. Employee perceptions of available AI resources, support, or governance represent the employee-level interface through which that capability becomes behaviorally relevant, but they should not be treated as equivalent to the organizational construct itself. Future empirical studies should therefore distinguish between measuring organizational AI capability as an organizational property and using employee perceptions as perceptual proxies. The former requires an explicitly multilevel design, whereas the latter should be interpreted as an employee-level perceptual model.

In public-sector organizations, enactment is further shaped by institutional accountability. AI-related resources may support service delivery, administrative responsiveness, and public value creation (Almheiri et al., 2025; van Noordt & Tangi, 2023), but employees must still integrate AI-supported work within legal mandates, procedural requirements, audit expectations, and due-process obligations. Organizational AI capability therefore becomes consequential not merely when resources are available, but when those resources can be translated into legitimate and accountable work practices.

Employee AI Learning as an Adaptive Mechanism

Employee AI learning is the first adaptive mechanism through which organizational AI capability becomes consequential at the employee level. It refers to the development of task-relevant knowledge and interpretive competence needed to understand how AI relates to work tasks, interpret AI-supported outputs, recognize when verification is required, and integrate AI-generated information with professional judgment (Kumar & Mittal, 2024; Leyer & Schneider, 2021).

This construct is intentionally narrower than adjacent concepts. Employee AI learning is not equivalent to formal training, because training is an organizational intervention whereas learning is the employee-level process that may result from training, experimentation, observation, or repeated use. It is also distinct from broad AI literacy, technology readiness, self-efficacy, and trust. Self-efficacy and trust may develop alongside learning and influence subsequent AI use, but they are not treated as constitutive dimensions of the construct.

Organizational AI capability is expected to facilitate employee AI learning by making AI-related resources accessible through relevant tools, guidance, learning opportunities, managerial support, and opportunities for practice. These conditions are treated as manifestations through which organizational capability reaches employees rather than as separate constructs in the formal model.

Organizational Learning Theory supports this competence-development process by explaining how knowledge develops through experience and reflection (Argyris & Schön, 1978), while Social Cognitive Theory helps explain why environmental support and opportunities for engagement facilitate learning (Bandura, 1986). Organizational AI capability therefore increases the conditions from which employee AI learning can emerge, although it does not imply that all employees will develop identical competence or that learning will automatically translate into

AI use.

Proposition 1: Organizational artificial intelligence capability positively influences employee AI learning.
Employee Unlearning as Routine Revision

Employee unlearning is the second adaptive mechanism through which organizational AI capability becomes enacted. It refers to the conscious revision or reduced reliance on path-dependent assumptions, habits, and routines that no longer fit AI-enabled work. Because unlearning has been criticized when conceptualized as literal or manageable knowledge erasure (Howells & Scholderer, 2016), the present framework adopts the narrower interpretation of reduced reliance on established assumptions and routines rather than literal forgetting. This interpretation is consistent with work that treats unlearning as a reduction in reliance on previously established ways of working under changed conditions (Tanaka, 2023; Wang et al., 2025).

Employee unlearning is also distinct from ordinary learning and double-loop learning. Learning primarily concerns acquiring or refining knowledge and competence, whereas unlearning concerns loosening commitment to previously established assumptions or routines. Double-loop learning involves questioning underlying governing assumptions more broadly (Argyris & Schön, 1978). In this framework, unlearning refers more specifically to revising path-dependent routines that impede AI-enabled work, with behavioral evidence reflected in reduced reliance on those routines in subsequent practice (Visser, 2017).

This distinction is especially important in public-sector organizations because not every established routine should be revised. Some routines persist mainly through habit, legacy systems, duplicated work sequences, or inherited administrative practice, whereas others perform legitimate legal, audit, documentation, fairness, or due-process functions (Busuioc, 2021). Unlearning therefore concerns path-dependent routines whose revision does not remove a necessary accountability safeguard.

Organizational AI capability can stimulate unlearning by making inconsistencies between existing routines and AI-enabled workflows more visible. AI-supported processes may expose redundant manual steps, duplicated information processing, or inherited sequences that no longer add substantive value. However, recognition of redundancy does not automatically lead to routine revision. Employees may retain established procedures when their accountability function or authorization to change them is unclear (Koddebusch et al., 2024).

Accordingly, organizational AI capability is expected to increase opportunities for employees to identify and reconsider path-dependent routines, while the strength of this relationship remains contingent on institutional conditions surrounding routine revision. Procedural rigidity is introduced later as a boundary condition expected to constrain this relationship more strongly than the corresponding relationship between organizational AI capability and employee AI learning.

Proposition 2: Organizational artificial intelligence capability positively influences employee unlearning of path-dependent routines that constrain AI-enabled work.

AI Use as Behavioral Enactment

AI use refers to employees' task-integrated application of AI tools, systems, or outputs in substantive work activities. It differs from organizational AI adoption, access, intention to use, or occasional experimentation because it concerns the actual incorporation of AI into recurring task execution (Albishri et al., 2026).

Employee AI learning is expected to increase AI use by developing the task-relevant competence needed to interpret AI-supported outputs, recognize when verification is required, and determine how AI-generated information should be incorporated into work (Kumar & Mittal, 2024; Leyer &

Schneider, 2021). Technology-acceptance perspectives help explain willingness to use technology, but willingness alone does not ensure that AI can be meaningfully integrated into task performance (Venkatesh et al., 2003).

Proposition 3: Employee AI learning positively influences task-integrated AI use.

Employee unlearning provides a complementary pathway. Employees may understand how AI works but continue to rely on path-dependent routines that duplicate, delay, or constrain its incorporation into work (Wang et al., 2025). By reducing reliance on such routines, unlearning creates greater scope for AI-supported work while preserving necessary accountability safeguards.

Proposition 4: Employee unlearning positively influences task-integrated AI use by reducing reliance on path-dependent routines that unnecessarily duplicate or constrain AI-supported work.

The framework does not include a direct organizational AI capability–AI use path in its core specification because its theoretical purpose is to explain the employee-level mechanisms through which organizational capability becomes enacted. This does not imply that a direct effect is impossible or that full mediation must occur empirically. Organizational resources or governance arrangements may also facilitate AI use directly, and future studies should compare models with and without this direct relationship.

Task-integrated AI use may be reflected in the extent, breadth, depth, or frequency with which AI is incorporated into work. Responsible verification, however, is treated as a governance requirement rather than as part of the AI-use construct itself. This distinction prevents frequent but inappropriate reliance on AI from being interpreted automatically as stronger enactment.

Employee Sustainable Performance in AI-Enabled Public Sector Work

Employee sustainable performance refers to employees' capacity to maintain effective, adaptive, and healthy performance over time (De Vos et al., 2020; Ji et al., 2021). It is selected as the focal outcome because the framework is concerned not only with immediate productivity gains, but with whether AI-supported work remains beneficial as employees adapt to changing technological demands.

Task-integrated AI use can support sustainable performance by reducing repetitive work, improving information processing, augmenting analytical capacity, and helping employees respond to complex administrative demands (Kulal et al., 2024; Qi et al., 2026). However, greater AI use does not necessarily improve sustainable performance uniformly. AI-supported work may also generate cognitive

burden, dependence, technostress, or uncertainty when employees do not understand the limits of AI outputs or the responsibilities associated with their use (Raisch & Krakowski, 2021; Zitar et al., 2023).

The positive relationship proposed here is therefore conditional on the net consequences of task-integrated AI use. AI use is expected to support sustainable performance when improvements in effectiveness and adaptability are not persistently outweighed by cognitive overload, dependence-related costs, or technostress that undermine healthy work functioning. Where such adverse costs dominate the task benefits of AI use, the net relationship may become negligible or negative.

Accountability clarity is therefore proposed as a key boundary condition. It refers to the extent to which employees understand who remains responsible for AI-supported work, what verification and documentation are required, and how errors or uncertain outputs should be escalated (Busuioac, 2021; Yuan & Chen, 2025). Accountability clarity addresses uncertainty about responsibility, verification, documentation, and escalation, but it should not be treated as a remedy for every potential cost of AI use. High clarity can reduce hesitation, defensive duplication, inappropriate overreliance, and stress arising specifically from ambiguous responsibility, while cognitive overload, dependence, or technostress may persist for other reasons. Accordingly, low accountability clarity is expected to weaken the positive AI use–employee sustainable performance relationship rather than inherently reverse it. A null or negative net effect would require the adverse consequences of AI use to outweigh its effectiveness and adaptability benefits.

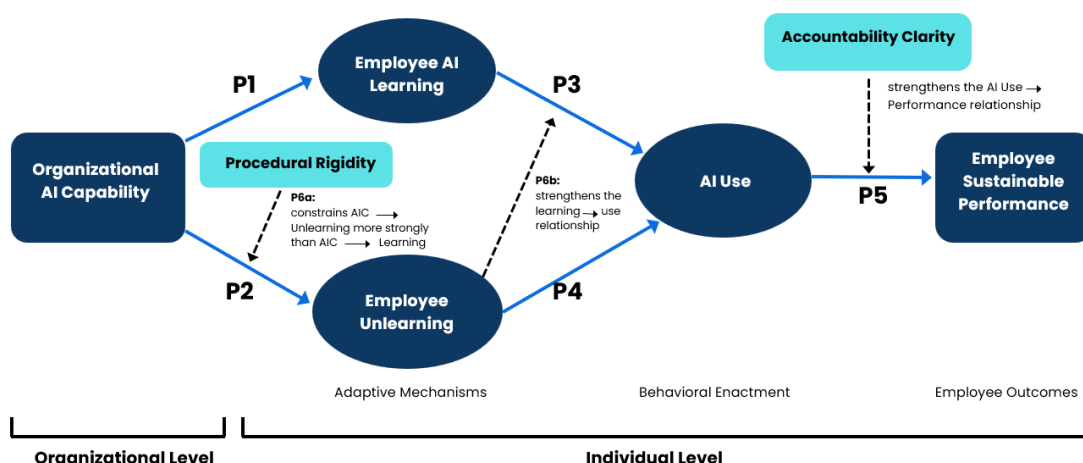
Public responsibility remains a scope condition rather than a dimension of employee sustainable performance. Improvements in efficiency or output that materially undermine legality, fairness, transparency, auditability, accountability, or due process should not be interpreted as successful enactment within the framework. Sustainable performance should therefore be assessed separately from indicators of responsible AI use and public accountability.

Proposition 5: Task-integrated AI use positively influences employee sustainable performance, and this relationship is stronger when accountability clarity is high.

Conceptual Framework and Boundary Conditions

The proposed framework explains how organizational AI capability becomes enacted through employee adaptation and task-integrated AI use in public-sector organizations. Organizational AI capability provides the organizational

Figure 1. Accountability-Bounded AI Capability Enactment Framework.



Source: Authors' conceptualization

resource base, while employee AI learning and employee unlearning represent distinct but complementary adaptive mechanisms. AI use constitutes the behavioral enactment stage through which these mechanisms become embedded in everyday work.

The two adaptive mechanisms are expected to face different institutional points of interruption. Employee AI learning can often proceed through sanctioned training, guidance, observation, knowledge sharing, and bounded experimentation without immediately changing an authorized workflow (Kumar & Mittal, 2024). Organizational-routine theory, however, emphasizes that routines are reproduced through recurring performances and that meaningful change requires variation in actual practice rather than knowledge acquisition alone (Pentland & Feldman, 2005). Unlearning similarly concerns deliberate reduction in reliance on established knowledge or routines rather than the simple addition of new knowledge (Koddebusch et al., 2024; Tsang & Zahra, 2008).

This difference becomes consequential in public organizations because routine revision can change how actions are authorized, documented, verified, audited, and attributed. AI can shift the locus of administrative discretion (Young et al., 2019), while accountability research emphasizes explanation, oversight, and answerability for algorithmically supported action (Busuioac, 2021). Recent research on blame avoidance further explains why public actors may become cautious when deviations from established practice increase visible responsibility exposure. Anticipatory blame avoidance can steer officeholders toward more risk-averse choices (Hinterleitner, 2023), and perceived blame risk has been linked to less prohibitive voice (Guo et al., 2026) and lower innovative behavior among public employees (Zhao et al., 2026). Approval requirements make this exposure explicit by attaching responsibility for a change in practice to identifiable actors, and can therefore interrupt unlearning at the point where recognition that a routine is obsolete would otherwise become an actual change in practice.

Procedural rigidity is therefore expected to weaken the relationship between organizational AI capability and employee unlearning more strongly than the corresponding relationship with employee AI learning. This differential prediction is conditional rather than absolute. It is expected where employees retain access to approved AI tools, training, guidance, or other learning opportunities while modification of established routines requires additional authorization or entails greater responsibility exposure. Procedural rigidity can also weaken employee AI learning when rules restrict access to AI systems, training, experimentation, or knowledge sharing. Under those conditions, the difference between its constraining effects on learning and unlearning should diminish and may disappear.

Proposition 6a: Where sanctioned AI learning opportunities remain available but routine revision requires additional authorization or entails greater responsibility exposure, procedural rigidity negatively moderates the relationship between organizational artificial intelligence capability and employee unlearning; this constraining effect is expected to be stronger than the corresponding effect on the relationship between organizational artificial intelligence capability and employee AI learning.

Learning and unlearning may also interact during behavioral enactment. Employee AI learning can increase competence without changing work behavior when employees remain dependent on established routines. Employee unlearning reduces this inertia by creating the cognitive and behavioral space required for newly acquired competence to be incorporated into actual work practice.

Proposition 6b: Employee unlearning positively moderates the relationship between employee AI learning and AI use, such that the positive relationship between employee AI learning and task-integrated AI use is stronger when employee unlearning is higher.

A further boundary condition operates between AI use and employee sustainable performance. As specified in Proposition 5, accountability clarity determines whether employees understand responsibility allocation, verification and documentation expectations, and escalation requirements surrounding AI-supported work. The framework therefore treats public-sector AI enactment as an accountability-bounded process in which organizational capability becomes consequential through employee adaptation and use, while the strength of key relationships depends on the institutional conditions surrounding enactment.

Methods

This study adopts a conceptual research design based on theory synthesis to explain how organizational AI capability becomes enacted through employee-level mechanisms in public-sector organizations. Theory synthesis is appropriate for integrating concepts and theoretical perspectives that have largely been examined in separate literature streams into a coherent explanatory framework (Jaakkola, 2020; MacInnis, 2011). Unlike a systematic literature review, the objective is not to exhaustively aggregate all studies within a predefined corpus, but to use theoretically relevant literature to clarify constructs, explain relationships and mechanisms, identify competing explanations, and specify boundary conditions. Literature-based approaches have also been employed in recent research on digital transformation and governance in the public sector (Zikri & Prasajo, 2026).

The literature identification process began with thematic searches conducted in November–December 2025 using Harzing's Publish or Perish with Google Scholar. To improve reproducibility, the principal thematic searches were rerun on June 2026 and retained as an auditable structured-search record. The structured search focused primarily on English-language publications from 2015 onward and served as a contemporary discovery base rather than a closed systematic-review corpus.

Eight thematic search combinations were used to capture the principal literature streams informing the framework. Table 1 reports the search combinations, raw retrieval counts from the June 2026 rerun, and the approximate number of substantive sources ultimately used from each stream. The categories overlap because individual sources can perform more than one theoretical function. In addition, Google Scholar returns a maximum of 1,000 results per query through Publish or Perish; raw counts approaching 1,000 therefore reflect the source retrieval ceiling rather than the full size of the underlying literature.

The raw search results were used as a discovery pool. Duplicate records were identified through DOI and title matching, after which records were examined for substantive relevance. Publications were eligible when they contributed directly to organizational AI or digital capability, employee learning or unlearning, workplace AI use, public-sector AI transformation and governance, microfoundational or dynamic-capability mechanisms, employee sustainable performance, or institutional conditions relevant to the proposed relationships. Studies focused exclusively on consumer adoption, student learning, clinical or patient applications, purely technical AI development, or sustainability without an organizational or employee-level connection were generally excluded unless they

Table 1. Structured Search Themes, Search Combinations, and Final Substantive Coverage

No.	Search theme	Search combination	Raw records	Approx. substantive sources used
1	AI capability	"artificial intelligence capability" OR "AI capability"	958	9
2	AI capability in public sector	("artificial intelligence capability" OR "AI capability") AND ("public sector" OR "public administration" OR "government")	960	8
3	AI use at work	("AI use" OR "AI usage" OR "artificial intelligence use") AND (employee OR workplace OR organization)	959	11
4	Employee learning	("employee learning" OR "workplace learning") AND ("artificial intelligence" OR "AI" OR "digital transformation")	968	6
5	Employee unlearning	("employee unlearning" OR "organizational unlearning") AND ("digital transformation" OR "artificial intelligence" OR "technology adoption")	689	9
6	Microfoundations / capability theory	microfoundations AND ("dynamic capabilities" OR "resource-based view" OR capability)	981	6
7	Sustainable employee outcomes	("sustainable employee performance" OR "sustainable employee outcomes" OR "employee sustainable performance")	915	8
8	Public-sector AI transformation / governance	("artificial intelligence" OR "AI") AND ("public sector" OR "public administration" OR "government") AND transformation	973	14

Table 2. Literature-to-Proposition Synthesis

Proposition	Literature basis & level	Inferred mechanism	Qualification & theoretical extension
P1 AIC → Employee AI learning	Mikalef & Gupta (2021); Kumar & Mittal (2024). Organization → employee.	Organizational AI capability provides resources, guidance, exposure, and learning opportunities from which task-relevant AI competence can develop.	Learning may vary across employees and does not automatically produce AI use. Extension: explicit cross-level prediction linking organizational AI capability to employee AI learning.
P2 AIC → Employee unlearning	Tsang & Zahra (2008); Koddebusch et al. (2024); Wang et al. (2025). Organization → employee.	AI-enabled possibilities expose misfit between established routines and changed work requirements, prompting reconsideration of path-dependent routines.	Only routines that unnecessarily constrain AI-enabled work are targeted; constitutive accountability safeguards remain outside the scope of unlearning. Extension: cross-level AIC → employee unlearning prediction.
P3 Employee AI learning → AI use	Kumar & Mittal (2024); Leyer & Schneider (2021). Employee → employee.	Learning develops the competence required to interpret, verify, and integrate AI-supported outputs into substantive work tasks.	Competence does not guarantee enactment when routines or organizational restrictions prevent use. Literature-informed; the outcome is refined here as task-integrated AI use.
P4 Employee unlearning → AI use	Koddebusch et al. (2024); Wang et al. (2025). Employee → employee.	Reduced reliance on obsolete or unnecessarily duplicative routines creates behavioral space for AI-enabled ways of working.	Unlearning without sufficient new competence may not produce effective use. Extension: prior unlearning mechanisms are applied specifically to task-integrated workplace AI use.
P5 AI use → ESP; Accountability clarity moderates	Ji et al. (2021); Raisch & Krakowski (2021); Busuioc (2021); Yuan & Chen (2025). Employee → employee; contextual moderator.	Task-integrated AI use can support effectiveness and adaptability, while accountability clarity reduces uncertainty about responsibility, verification, documentation, and escalation.	Cognitive burden, dependence, and technostress may offset task benefits. Main AI use–performance logic is literature-informed; accountability clarity as moderator is an author-derived boundary prediction.
P6a Procedural rigidity asymmetry	Pentland & Feldman (2005); Tsang & Zahra (2008); Busuioc (2021); Young et al. (2019). Institutional condition → cross-level relationships.	Competence acquisition can often occur within authorized arrangements, whereas routine revision more directly implicates discretion, approval, documentation, and responsibility exposure.	Rigidity can also constrain learning when access, training, or experimentation is restricted. The stronger constraining effect on unlearning than learning is a new theoretical conjecture.
P6b Employee unlearning × Employee AI	Visser (2017); Wang et al. (2025). Employee-level interaction.	Learning supplies competence, while unlearning reduces behavioral inertia that can prevent newly developed	Mandated workflows may produce use even with limited individual unlearning. The moderating

Proposition	Literature basis & level	Inferred mechanism	Qualification & theoretical extension
learning → AI use		competence from entering actual work practice.	relationship is an author-derived theoretical extension.

supplied a concept or mechanism necessary for the theoretical argument.

Because this is a conceptual theory-synthesis paper, literature identification was not restricted mechanically to the contemporary search window. Foundational constructs and mechanisms used in the framework originate partly in scholarship published more than ten years ago. The authors therefore conducted targeted manual searches through Scopus and ScienceDirect and followed relevant sources through publisher and scholarly platforms, including SpringerLink, Emerald Insight, SAGE Journals, Taylor & Francis Online, and JSTOR, together with backward and forward citation tracking. These searches were used particularly for the Resource-Based View, Dynamic Capabilities Theory, Organizational Learning Theory, Social Cognitive Theory, technology enactment, organizational and employee unlearning, public-sector accountability, administrative discretion, procedural rigidity and red tape, and competing technology-acceptance and readiness perspectives.

Targeted searches and citation tracing continued during framework refinement through June 2026. Search terms were adapted to the theoretical issue being examined and included combinations such as “resource-based view,” “dynamic capabilities,” “organizational learning,” “social cognitive theory,” “technology enactment,” “organizational routines,” “organizational unlearning,” “employee unlearning,” “public-sector accountability,” “administrative discretion,” “procedural rigidity,” “red tape,” “technology acceptance,” and “technology readiness,” together with AI-, digital-transformation-, employee-, and public-sector-related terms where appropriate. Selection for the final synthesis was theory-driven rather than based on bibliometric frequency or a predetermined screening quota. A source was retained when it performed a clear theoretical function by defining or distinguishing a focal construct, explaining a mechanism, clarifying the level of analysis, providing relevant empirical evidence, identifying a boundary condition, or offering a competing or qualifying explanation.

To make proposition development transparent, Table 2 summarizes how the principal literature arguments were translated into the proposed relationships. The table distinguishes relatively direct literature support from literature-informed extensions and author-derived theoretical conjectures. The latter are presented as propositions requiring subsequent empirical testing rather than as relationships already established by the cited studies.

The matrix also clarifies alternatives considered during framework development. A direct organizational AI capability–AI use relationship remains a plausible alternative specification but is excluded from the core framework because the theoretical objective is to explain employee-level enactment mechanisms. Technology acceptance and technology readiness are retained as competing explanatory perspectives but not as focal constructs because they primarily explain willingness or predisposition toward technology rather than the cross-level translation of organizational capability into work practice. Public responsibility remains a scope condition rather than a dimension of employee sustainable performance because legality, fairness, auditability, and due process concern the legitimacy of enactment rather than the definition of individual performance itself.

Result and Discussion

Conceptual Contribution of the Framework

The framework developed in this article addresses a cross-level problem in AI-enabled public-sector work: organizational AI capability may be present without producing corresponding changes in employee work practices. AI capability research establishes that value depends on the orchestration of technological, data, human, managerial, and governance resources rather than on technology possession alone (Mikalef & Gupta, 2021). The present framework extends this logic by specifying how such organizational capability becomes consequential at the employee level through employee AI learning, employee unlearning, and task-integrated AI use.

This explanation differs from conventional technology-acceptance and technology-readiness perspectives. Acceptance models primarily explain whether individuals intend to adopt or use technology based on factors such as perceived usefulness, ease of use, social influence, or facilitating conditions (Venkatesh et al., 2003), whereas readiness perspectives emphasize individual predispositions toward new technology (Peng & Yan, 2022). These perspectives remain relevant, but they address a different question. The present framework begins with an organizational capability and explains how organizational resources are translated into employee adaptation and actual work practices.

The distinction generates an empirically meaningful prediction. Employees may have access to AI, hold positive attitudes toward it, and intend to use it while still relying on established work routines that keep AI peripheral to substantive task execution. Conversely, organizations with substantial AI capability may obtain limited enactment when employees lack task-relevant competence or remain constrained by routines that were developed before AI was introduced. The framework therefore shifts attention from acceptance alone toward the mechanisms through which organizational AI capability becomes embedded in work.

The contribution is consequently not that prior research has ignored learning, unlearning, technology use, or employee adaptation. Rather, it lies in specifying how these elements operate within a cross-level enactment process and in deriving conditional predictions about when organizational AI capability becomes translated into AI use and sustainable employee performance.

Construct Clarification

The framework combines constructs that are related but perform different theoretical functions. Maintaining their conceptual boundaries is therefore important for both theoretical coherence and subsequent empirical testing. Table 3 summarizes their meaning, level of analysis, theoretical role, distinction from adjacent constructs, and indicative operational domain.

These distinctions also imply specific discriminant-validity requirements. Employee AI learning and employee unlearning should not be represented by interchangeable indicators because the former concerns competence acquisition whereas the latter concerns reduced reliance on established assumptions and routines. Procedural rigidity and accountability clarity should likewise remain distinct: the former concerns constraints on changing routines, while the latter concerns clarity about responsibility for AI-supported work. Future empirical studies should therefore test these boundaries against adjacent constructs such as AI literacy,

Table 3. Construct Clarification

Construct	Meaning in this framework	Level and theoretical role	Distinction from related constructs	Indicative operational domain
Organizational AI capability	The organizational capacity to orchestrate AI-related technological, data, human, managerial, and governance resources for AI-enabled work and organizational objectives (Mikalef & Gupta, 2021).	Organizational-level antecedent.	Not equivalent to ownership of AI tools, formal AI adoption, or individual AI competence. The construct concerns the orchestration of complementary organizational resources.	AI-related technological and data resources, human expertise, managerial coordination, and governance arrangements. Existing AI-capability measures provide the primary basis for operationalization; when assessed through employee perceptions, such measures should be interpreted as perceptual proxies of organizational capability rather than as direct individual-level measures.
Employee AI learning	Development of task-relevant knowledge and interpretive competence required to understand, evaluate, and incorporate AI into work (Kumar & Mittal, 2024; Leyer & Schneider, 2021).	Employee-level adaptive mechanism.	Distinct from formal training, broad AI literacy, technology readiness, self-efficacy, and trust. Training may enable learning, while self-efficacy and trust are related psychological states rather than constitutive dimensions of the construct.	Acquisition and development of task-relevant AI knowledge, competence in interpreting AI-supported outputs, recognition of when verification is required, and ability to integrate AI-generated information with professional judgment. Future measures should capture learning and competence development rather than participation in training alone.
Employee unlearning	Conscious revision or relinquishment of path-dependent assumptions, habits, and routines that unnecessarily constrain AI-enabled work (Tanaka, 2023; Visser, 2017; Wang et al., 2025).	Employee-level adaptive mechanism and moderator of the employee AI learning–AI use relationship.	Not literal forgetting. Distinct from learning because its object is an established assumption or routine rather than additional knowledge. Double-loop learning is an adjacent and partially overlapping process, but unlearning here refers specifically to relinquishing or revising path-dependent routines. Constitutive accountability routines are outside its scope.	Revision of obsolete assumptions, reduced reliance on path-dependent routines, and actual modification or relinquishment of practices that no longer fit AI-enabled work.
AI use	Task-integrated application of AI tools, systems, or outputs in substantive work activities, rather than organizational adoption or mere access to AI (Albishri et al., 2026).	Employee-level behavioral enactment mechanism.	Distinct from organizational AI adoption, access, intention to use, or occasional experimentation. The defining feature is the incorporation of AI into actual work tasks.	Extent and depth of AI integration into substantive work activities, including analysis, information processing, decision support, content generation, and service-related tasks. Frequency of use may be considered as an additional indicator but should not be interpreted independently from task integration.
Employee sustainable performance	Employees' capacity to maintain effective, adaptive, and healthy performance over time (De Vos et al., 2020; Ji et al., 2021).	Employee-level outcome.	Broader than short-term productivity or efficiency. Public responsibility is treated as a scope condition rather than a dimension of the performance construct.	Sustained effectiveness, adaptability to changing work demands, and healthy work functioning over time.
Procedural rigidity	Conceptualized in this study as the extent to which formal rules, approval requirements, audit expectations, and	Public-sector boundary condition constraining the organizational AI capability–	Related to but distinct from red tape and formalization. Red tape concerns burdensome rules that fail to serve their intended purpose (Bozeman & Feeney, 2011), whereas	Perceived discretion to revise routines, approval constraints, audit exposure, procedural inflexibility, and perceived sanction risk associated with routine change. Future research should develop and validate appropriate

Construct	Meaning in this framework	Level and theoretical role	Distinction from related constructs	Indicative operational domain
	sanction risks restrict employee discretion to revise established work routines.	employee unlearning relationship more strongly than the learning relationship.	procedural rigidity may arise even from legitimate rules that constrain discretion to revise established routines.	measures and establish discriminant validity against red tape and formalization.
Accountability clarity	Conceptualized in this study as the extent to which employees understand who remains responsible for AI-supported work, what verification and documentation are required, and how errors or uncertain outputs should be escalated (Busuioc, 2021; Yuan & Chen, 2025).	Public-sector boundary condition affecting the AI use–employee sustainable performance relationship.	Distinct from general governance quality, managerial support, role clarity, and procedural rigidity. Accountability clarity concerns responsibility allocation and expectations specifically associated with AI-supported work rather than general understanding of one's job responsibilities.	Clarity of responsibility assignment, verification expectations, documentation requirements, human-oversight points, and escalation procedures for AI-supported work. Future research should develop and validate appropriate measures and establish discriminant validity against general role clarity and broader governance constructs.

technology readiness, double-loop learning, red tape, formalization, and general role clarity.

From Organizational AI Capability to Employee Enactment

The Resource-Based View and Dynamic Capabilities Theory explain why AI-related resources must be assembled and reconfigured to generate value (Barney, 1991; Teece et al., 1997), but they provide less specificity regarding how organizational capability becomes translated into employee behavior. The present framework specifies two employee-level adaptive mechanisms that perform different functions in this translation.

Employee AI learning develops the competence needed to interpret AI-supported outputs and incorporate them into work. Employee unlearning addresses a different problem: employees may acquire new AI-related competence while continuing to rely on established routines that prevent that competence from changing actual practice. Learning without unlearning can therefore produce knowledgeable employees whose work remains behaviorally anchored in pre-AI routines, while unlearning without sufficient learning may create openness to change without the competence required for effective AI use.

AI use represents the behavioral stage at which these adaptations become enacted. It is therefore defined as task-integrated use rather than access, organizational adoption, experimentation, or intention. The framework foregrounds the mediated pathways from organizational AI capability to AI use because its theoretical purpose is to explain employee-level enactment. This does not exclude a direct organizational AI capability–AI use relationship. Organizational resources may directly facilitate use, particularly where AI is embedded in mandatory workflows, and future empirical research should compare mediated and direct-effect specifications.

Learning, Unlearning, and the Asymmetry of Public-Sector Adaptation

The central theoretical distinction concerns the institutional conditions under which learning and unlearning occur. Both support adaptation, but they do not carry equivalent organizational consequences in public-sector settings. Learning can often occur without changing existing procedures. Employees may receive training, guidance, or

opportunities for experimentation while formal work arrangements remain intact. Unlearning differs because revising a routine may affect established arrangements for authority, documentation, verification, and responsibility. The distinction is therefore not that public employees are inherently resistant to change, but that routine revision can create greater authorization and accountability exposure than competence acquisition.

This logic requires distinguishing path-dependent routines from constitutive accountability routines. Path-dependent routines persist primarily because they are historically embedded, familiar, or inherited even when they no longer add substantive value. Constitutive accountability routines, by contrast, perform identifiable legal, audit, documentation, fairness, or due-process functions. Employee unlearning in this framework applies to the former rather than to the abandonment of legitimate safeguards.

Procedural rigidity explains when this distinction becomes consequential. Rules, approvals, audit requirements, and sanction arrangements may serve legitimate public purposes, yet they can also restrict discretion to redesign work. Organizational AI capability may therefore continue to stimulate employee learning through exposure, guidance, and access while generating weaker unlearning when employees perceive greater risks associated with altering established procedures. This produces the predicted asymmetry: procedural rigidity should constrain the organizational AI capability–employee unlearning relationship more strongly than the corresponding relationship with employee AI learning.

The asymmetry should weaken where procedural arrangements already grant explicit, formally authorized discretion to redesign workflows or where revised AI-enabled procedures have been institutionally approved. Conversely, where the same rules also restrict access to AI systems, training, experimentation, or knowledge sharing, procedural rigidity can constrain learning as well, reducing or eliminating the predicted differential effect.

AI Use, Accountability Clarity, and Employee Sustainable Performance

Technology-enactment perspectives establish that technologies become consequential through situated use rather than formal availability alone (Fountain, 2001;

Orlikowski, 2000). The present framework extends this logic to AI-enabled public-sector work by emphasizing that the consequences of AI use depend on how responsibility surrounding that use is organized.

Task-integrated AI use can support sustainable employee performance by reducing repetitive effort, improving information processing, augmenting analytical capacity, and supporting adaptation to changing work demands. These benefits, however, cannot be assumed to arise uniformly. Employees may remain uncertain about who holds final responsibility for AI-supported decisions, what verification is required, how AI contributions should be documented, or how uncertain outputs should be escalated.

Accountability clarity addresses responsibility uncertainty without eliminating all burdens associated with AI-supported work. High clarity should strengthen the positive relationship between task-integrated AI use and sustainable employee performance by reducing hesitation, defensive duplication, and stress associated with ambiguous responsibility, verification, documentation, and escalation expectations. This mechanism is especially relevant to the healthy dimension of sustainable performance because ambiguity over responsibility can itself become a source of strain. However, accountability clarity does not remove cognitive overload, technology dependence, or technostress arising from other features of AI-enabled work. Low clarity is therefore expected to weaken rather than automatically reverse the relationship; a null or negative net effect would require adverse costs of AI use to outweigh its task-related benefits.

Theoretical Implications

First, it extends AI capability research from organizational resource orchestration to cross-level enactment. AI capability provides the organizational resource base, while employee AI learning, employee unlearning, and AI use explain how that capability becomes behaviorally consequential. Organizations with comparable AI capability may therefore produce different employee outcomes when the quality of adaptation and enactment differs.

Second, the framework extends organizational-learning and capability-reconfiguration logic by assigning employee unlearning a dual role. Unlearning is not only a parallel adaptive pathway alongside employee AI learning; it is also theorized to condition the extent to which newly developed competence becomes behaviorally consequential in task-integrated AI use. This conditioning role differentiates the framework from prior parallel-mediation treatments of learning and unlearning.

Third, the framework specifies a conditional public-sector learning-unlearning asymmetry. Competence acquisition and routine revision are both adaptive, but they encounter different institutional points of interruption. Where sanctioned learning opportunities remain available, procedural rigidity is expected to constrain routine revision more strongly because changing established practice may require additional discretion, authorization, and responsibility exposure. The asymmetry is not assumed to hold where the same procedural arrangements also substantially restrict learning opportunities.

Fourth, the framework extends technology-enactment logic into an accountability-bounded AI context. Accountability clarity is expected to strengthen the positive relationship between task-integrated AI use and sustainable employee performance by reducing responsibility-related uncertainty around verification, documentation, and escalation. This mechanism does not imply that accountability clarity eliminates cognitive burden, dependence, or technostress associated with AI use.

Together, these extensions shift attention from whether

public organizations possess sufficient AI resources to whether those resources can be enacted through competence development, routine revision, task-integrated use, and sufficiently clear accountability arrangements.

Practical Implications

The framework has practical implications for how public-sector organizations manage AI-enabled transformation. For senior leaders and digital-transformation units, AI capability should not be assessed solely through technology acquisition, infrastructure, or system deployment. Implementation indicators should also capture whether employees develop task-relevant competence, whether appropriate routines are redesigned, and whether AI becomes integrated into substantive work.

For human-resource and learning functions, conventional training should be complemented by task-based learning activities, including scenario-based verification exercises, interpretation of AI-supported outputs, and periodic competence reassessment. These interventions should develop employees' ability to identify when verification is required and to integrate AI-generated information with professional judgment. At the same time, organizations should create structured opportunities to identify routines that no longer add value while distinguishing them from procedures that perform legitimate accountability functions.

For line managers and process owners, procedural rigidity highlights the importance of sanctioned discretion. Employees should know which workflow elements may be revised, who has authority to approve changes, which documentation must be retained, and when supervisory or governance review is required. Routines that mainly duplicate work or preserve inherited manual sequences without serving identifiable legal, audit, documentation, fairness, or due-process functions are stronger candidates for redesign.

For AI-governance, audit, and risk-management functions, accountability clarity should be translated into concrete arrangements. These may include responsibility matrices, documented human-oversight points, verification requirements for consequential outputs, documentation standards, escalation procedures, audit trails, and periodic review of responsibility allocation as AI systems and work processes evolve.

The framework therefore does not imply that public organizations should simply maximize AI use. The practical objective is to align organizational AI capability, employee competence development, routine revision, task-integrated AI use, and accountability arrangements so that AI supports sustainable employee performance without weakening the institutional safeguards that legitimate public-sector work.

Limitations and Future Research Directions

This article develops a conceptual framework whose propositions remain to be empirically tested. Future studies should examine the proposed pathways from organizational AI capability through employee AI learning and employee unlearning to task-integrated AI use and employee sustainable performance, including the moderating roles of procedural rigidity, employee unlearning, and accountability clarity. Alternative specifications incorporating a direct organizational AI capability-AI use relationship should also be compared.

The framework combines an organizational-level antecedent with employee-level mechanisms and outcomes. Organizational AI capability remains an organizational construct, whereas employee AI learning, employee unlearning, AI use, and employee sustainable performance operate at the individual level. Studies using employee perceptions of organizational AI capability should therefore interpret them as perceptual proxies, while research treating AI capability as a shared organizational property should employ appropriate

aggregation and multilevel designs.

Several constructs also require further empirical validation. Employee AI learning should remain distinct from AI literacy, technology readiness, self-efficacy, and general workplace learning, while employee unlearning should be distinguished from double-loop learning and general routine change. Procedural rigidity and accountability clarity likewise require measurement development and discriminant-validity testing against adjacent constructs such as red tape, formalization, general role clarity, and broader governance quality.

The formal conditioning variables specified in the framework are procedural rigidity, employee unlearning, and accountability clarity. Other organizational characteristics, such as digital maturity, leadership support, learning climate, AI transparency, or risk tolerance, remain outside the present model and should be treated as exploratory extensions rather than implied boundary conditions.

Public responsibility is treated as a scope condition rather than as a dimension of employee sustainable performance. Future research could therefore examine failed or inappropriate enactment as a distinct outcome, including persistent non-use despite available capability, inappropriate reliance on AI, or accountability failures. Although the learning and unlearning mechanisms may also be relevant beyond public organizations, the boundary logic developed here is specifically theorized for settings in which legality, auditability, procedural requirements, and public accountability materially shape employee discretion.

Finally, the framework represents a primarily static enactment process. Longitudinal research could examine whether repeated AI use feeds back into subsequent learning and unlearning, alters reliance on AI, or contributes to further organizational capability reconfiguration. Because the theory synthesis relies on purposive literature selection and author judgment, it also remains subject to selection and confirmation bias. Future systematic or bibliometric reviews could complement the present synthesis by examining the broader distribution and evolution of evidence across these domains.

Conclusion

This article addresses why organizational AI capability may coexist with limited change in employee work practices. Organizational AI capability provides the organizational resource base, while employee AI learning develops task-relevant competence, employee unlearning reduces reliance on path-dependent routines, and task-integrated AI use represents behavioral enactment. The distinctive contribution lies in specifying how these mechanisms operate conditionally rather than in simply combining learning and unlearning. Employee unlearning is theorized to strengthen the translation of AI learning into task-integrated use; procedural rigidity is expected to constrain capability-driven unlearning more strongly than learning where sanctioned learning remains available; and accountability clarity strengthens the relationship between AI use and employee sustainable performance. These propositions remain theoretically derived and require empirical testing. Together, they shift AI capability research from resource possession toward a more explicit explanation of how organizational capability becomes enacted through employee adaptation,

routine revision, situated use, and public-sector institutional conditions.

The framework therefore extends AI capability research from organizational resource possession toward cross-level enactment without redefining organizational AI capability as an individual construct. It also specifies how public-sector accountability shapes the translation of organizational capability into employee adaptation, behavior, and performance. Successful AI enactment cannot consequently be assessed through technology availability, use, or productivity alone; it depends on whether employees can develop relevant competence, revise appropriate routines, integrate AI into substantive work, and remain clearly accountable for AI-supported actions. Organizational AI capability creates the potential for AI-enabled transformation, but its employee-level value ultimately depends on how that potential is enacted within the institutional conditions of public-sector work.

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Declarations

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