

ARTIFICIAL INTELLIGENCE AND ORGANIZATIONAL TRANSFORMATION

GOVERNANCE, ADOPTION, AND
FUTURE WORKFORCE SKILLS

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PREFACE

Artificial intelligence is no longer a subject discussed only by engineers or technology departments. It has begun to enter the ordinary spaces of organizational life: reports drafted in minutes, decisions supported by algorithms, institutional knowledge retrieved through digital systems, and employees expected to learn new tools while continuing to carry the responsibilities of their roles. For organizations, this change raises a question that is deeper than adoption alone: how can artificial intelligence be used in ways that strengthen judgment, learning, trust, and responsibility?

The rapid spread of generative and decision-support technologies has made organizational change more visible and more urgent. These tools can help institutions document knowledge, test alternatives, improve access to information, and support faster decisions. Yet the same tools can also produce uncertain outputs, repeat outdated assumptions, weaken critical review, or make organizations appear more prepared than they truly are. For this reason, the future of artificial intelligence in organizations cannot be understood only through speed, efficiency, or automation. It must also be considered through governance, human capability, institutional memory, and the quality of learning.

This book brings together these concerns under the broader theme of organizational transformation. The first chapter examines organizational learning, unlearning, and skills renewal in the age of generative AI, emphasizing the need to verify machine-assisted knowledge and to renew human judgment alongside technical use. The second chapter focuses on institutional memory, adaptive capacity, and organizational resilience, showing how memory can become a source of strength when it is preserved with context, ownership, and care. The third chapter turns to human capital and AI adoption, using survey evidence to explore how workforce characteristics shape the use of AI tools. The fourth chapter examines data governance and cost as determinants of AI-based decision support adoption, highlighting that trust and data arrangements may matter as much as, and sometimes more than, technical performance.

Across these chapters, the book approaches artificial intelligence not as a distant or abstract technology, but as something that becomes meaningful inside real organizational routines. It asks how people

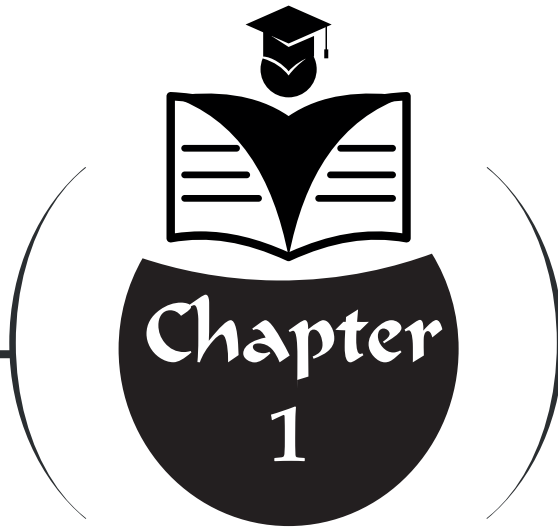
learn with AI, how institutions remember through digital systems, how employees differ in their readiness to use new tools, and how organizations decide whether an AI-supported system is worth adopting. In doing so, the book aims to keep the human and managerial dimensions of artificial intelligence at the center of the discussion.

It is hoped that this work will be useful to researchers, academics, managers, policy makers, human resources professionals, and all readers interested in the organizational consequences of artificial intelligence. More broadly, the book invites readers to think of AI not as a replacement for human responsibility, but as a field in which responsibility must be designed more carefully. If artificial intelligence is to contribute to stronger organizations, it must be accompanied by sound governance, trustworthy data practices, thoughtful learning systems, and a continuing commitment to human judgment.

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ORGANIZATIONAL LEARNING,
UNLEARNING, AND SKILLS
RENEWAL IN THE AGE OF
GENERATIVE AI

Introduction

This chapter makes two related contributions to the literature on management and organization in the AI era. First, it extends classic organizational learning theory into a context in which knowledge can be generated at high speed by a nonhuman system embedded in everyday work. That extension matters because the velocity, fluency, and low marginal cost of GenAI change the economics of codification and reuse. A draft memo, a policy summary, a training outline, or a client response can now be produced in seconds and circulated widely before its quality has been established. The organization's learning problem therefore shifts from simply creating and transferring knowledge to governing how machine-mediated content becomes accepted, stored, and repeated across units (Levitt & March, 1988; Walsh & Ungson, 1991; Argote, 2013).

Second, the chapter reframes capability development as a combined process of learning, unlearning, and verification. In earlier technology transitions, organizations often struggled because they lacked information or because expertise remained localized. In the GenAI context, organizations may face the opposite problem: too much plausible content, too many candidate routines, and too little disciplined review. This is why learning agility cannot be reduced to training completion or tool access alone. It must include the capacity to question machine output, retire outdated routines, and preserve human judgment under conditions of speed and ambiguity (March, 1991; Tsang & Zahra, 2008; Raisch & Krakowski, 2021).

Organizational learning has long been understood as the process through which experience is converted into routines, shared interpretations, and performance improvements (Argyris & Schon, 1978; Levitt & March, 1988; Argote, 2013). In this tradition, organizations learn by creating, retaining, transferring, and institutionalizing knowledge across individuals, groups, and formal structures. They also build memory: a stock of rules, templates, stories, procedures, databases, and role expectations that enables coordinated action over time (Walsh & Ungson, 1991).

Generative AI changes the pace, visibility, and quality profile of these processes. Knowledge is no longer produced only through observation, reflection, conversation, and codification carried out by humans. It is increasingly drafted, summarized, classified, retrieved, and recombined by machine systems that participate in everyday work. As a result, organizations can externalize tacit know-how more rapidly, reduce search costs, and accelerate documentation. Yet the same systems can produce plausible but incorrect output, flatten nuance, and create a false sense of certainty around content that has not been validated (Bender et al., 2021; Ji et al., 2023). Recent

reviews similarly show that AI implementation reconfigures work, governance, and role expectations across organizational levels (Lee et al., 2023; Bankins et al., 2024).

This shift matters because organizational learning is never only about accumulation. It is also about selection: what gets noticed, what gets repeated, what becomes the preferred template, and what is eventually remembered as the correct way to do things. When GenAI enters a workflow, these selection processes accelerate. Teams can produce more recommendations, summaries, and artifacts with less effort, but speed can conceal weak judgment. In effect, organizations may scale documentation before they scale understanding.

For that reason, a contemporary discussion of organizational learning in the age of AI cannot stop at acquisition or upskilling. It must also explain how organizations unlearn obsolete routines, how they avoid competency traps, how they treat AI as an active participant in memory formation, and how they design performance systems that reward disciplined experimentation rather than punishing every deviation (March, 1991; Sitkin, 1992; Tsang & Zahra, 2008).

The chapter proceeds in six steps. First, it explains why classic learning mechanisms change once GenAI enters daily work. Second, it shows why unlearning is a central managerial task rather than a secondary adjustment. Third, it examines how hallucination risk and competency traps interact. Fourth, it reconceptualizes GenAI as an active actor in organizational memory formation. Fifth, it proposes operational indicators for learning agility and adaptive capacity. Finally, it addresses how performance systems can enable safe experimentation instead of suppressing it.

Accordingly, the chapter argues that resilient organizations in the GenAI era are not those that automate the fastest. They are those that learn and unlearn deliberately, verify machine-assisted knowledge before institutionalizing it, and redesign their performance systems so that experimentation, correction, and skills renewal can occur without generating chaos. In this view, organizational learning becomes inseparable from memory quality, error governance, and adaptive capacity.

Why Organizational Learning Changes Under Generative AI

A useful way to interpret this shift is through the classic tension between exploration and exploitation. GenAI dramatically lowers the cost of exploration by making it easy to test alternatives, compare draft formulations, and simulate possible responses. Yet the same capability can produce premature exploitation when one machine-generated output is copied widely before it has been validated in context. What appears to be efficiency may therefore be the

early stabilization of an unreliable routine. In this sense, GenAI compresses the temporal distance between variation and institutionalization, making managerial review more important, not less important (March, 1991).

This compression also changes where organizational learning happens. Instead of being concentrated in formal training sessions or post-project reviews, learning increasingly occurs in the micro-practices of prompting, editing, checking, annotating, and sharing outputs. These small acts matter because they determine whether the organization develops a trustworthy memory ecology or a brittle one. When employees explain why an output was corrected, label reusable prompts, and document the conditions under which AI suggestions are acceptable, they create not only better immediate outcomes but also higher-quality memory traces for future work (Nonaka, 1994; Nonaka & Takeuchi, 1995).

Classic organizational learning research emphasized experience, routines, search, interpretation, and memory (Levitt & March, 1988). Generative AI alters each of these mechanisms. Experience becomes partly synthetic because employees now interact not only with customers, colleagues, and information systems, but also with machine-generated suggestions. Search becomes easier but also noisier because retrieval is filtered through probabilistic generation. Interpretation becomes more fragile because polished language can create an illusion of validity. Memory becomes more dynamic and more unstable when codification is continuously assisted by systems that summarize and recombine content at scale.

At the same time, GenAI expands the organization's ability to externalize and circulate tacit knowledge. Prompt libraries, transcript summaries, meeting recaps, decision logs, and AI-assisted drafting tools help transform dispersed know-how into shareable artifacts more quickly than before. This development echoes earlier arguments in knowledge-creation theory that organizations generate value by converting tacit knowledge into explicit forms that can travel across contexts (Nonaka, 1994; Nonaka & Takeuchi, 1995). However, faster codification does not automatically produce better learning. Without interpretation, testing, and revision, organizations may scale artifacts before they scale judgment.

The managerial challenge, therefore, is not simply adoption. It is governing the relationship between speed and validity. A firm that generates and stores machine-assisted content rapidly may appear adaptive, but if it lacks routines for review, correction, and retirement of obsolete templates, it may be building a brittle memory system. This is especially important when teams begin to substitute AI-generated fluency for collective reflection. What appears to be efficiency can quietly become epistemic drift: the slow migration of shared

understanding away from verified practice.

Research on AI and management reinforces this tension. Raisch and Krakowski (2021) describe AI as creating an automation-augmentation paradox: organizations can use AI either to substitute for human judgment or to extend it, but each path creates distinct managerial consequences. Likewise, Jarrahi (2018) argues that human-AI symbiosis is most valuable in decision contexts marked by uncertainty and equivocality, where machine assistance needs human interpretation rather than simple acceptance. These insights suggest that GenAI should not be framed as a knowledge engine on its own. Its organizational value depends on how learning routines are designed around it.

In practical terms, this means that organizational learning under GenAI becomes a design problem. Leaders must specify what kinds of knowledge can be drafted by AI, what must be verified by domain experts, where human sign-off is required, and how corrections are fed back into templates, prompts, and repositories. If those design choices remain implicit, organizations risk confusing content generation with learning capacity.

A further change concerns temporal rhythm. Traditional learning cycles were often visible through projects, reviews, and after-action reflection. GenAI compresses those cycles. Drafting, summarization, and recombination happen in real time, sometimes inside routine interactions rather than at the end of them. This compression creates a managerial temptation to treat immediate output as evidence of immediate learning. Yet fast production is not the same as deep assimilation. Organizations still need interpretive pauses in which teams ask what should be believed, what should be retained, and what should be discarded.

GenAI also changes who participates in learning. Previously, memory formation depended mainly on role holders, experts, documents, and routines. Now it is distributed across human workers, digital systems, prompt libraries, retrieval infrastructures, and model outputs. This broader configuration means that learning must be understood as a socio-technical accomplishment rather than a purely human one. The more organizations ignore that point, the more likely they are to overestimate capability simply because output volume has increased.

Organizational Unlearning and the Retirement of Obsolete Routines

For this reason, unlearning should be treated as a designed managerial process rather than as a spontaneous by-product of innovation. Organizations often assume that new tools will naturally displace old habits. In practice, legacy routines linger because they are embedded in templates, onboarding

documents, approval chains, reward systems, and informal expectations. Even after a workflow is officially replaced, employees may still rely on obsolete checklists or inherited phrasing because those artifacts remain cognitively available and socially legitimate. Unlearning therefore requires active removal, relabeling, and de-authorizing of outdated guidance, not just announcement of a new method (de Holan & Phillips, 2004; Tsang & Zahra, 2008).

Managers can support such retirement processes through what might be called memory hygiene. This includes version control for reusable artifacts, expiration dates for prompts and templates, clear ownership for policy documents, and periodic audits of what employees actually reuse in daily work. Memory hygiene is especially important in GenAI-enabled contexts because old human-generated routines and newly generated machine routines can coexist and conflict. Without disciplined pruning, organizations accumulate an archive that is large but not reliable, and employees become less able to distinguish historically important knowledge from operationally valid knowledge. Recent research on computer-based organizational memory and learning from failure further suggests that digital repositories improve adaptation only when they are actively curated and tied to correction processes (Nagayoshi & Nakamura, 2024).

One of the weakest habits in AI enthusiasm is the assumption that organizations only need to learn more. In reality, they also need to stop doing certain things. Organizational unlearning refers to the deliberate abandonment of beliefs, routines, or practices that no longer fit the environment or that actively impede adaptation (Tsang & Zahra, 2008). In AI-enabled contexts, unlearning becomes essential because new tools are rarely inserted into a neutral system. They enter organizations that already possess legacy workflows, deeply embedded assumptions, and historically reinforced ways of defining expertise.

The problem is well captured by March's (1991) distinction between exploration and exploitation. Organizations tend to exploit what has worked before because success stabilizes routines and makes them efficient. Yet the same routines can become obstacles when the environment changes. Leonard-Barton (1992) described this tension as the paradox of core capabilities and core rigidities: strengths that once produced competitive advantage can later limit adaptation. GenAI sharpens this paradox because it often appears compatible with existing routines while quietly altering the assumptions beneath them. An organization may keep the same reporting process, review cycle, or customer-support script, but the knowledge entering that process may now be machine-generated, probabilistic, and context-sensitive in new ways.

Unlearning, then, is not the opposite of learning. It is a condition for higher-quality learning. It involves identifying routines that should no longer be preserved, challenging taken-for-granted templates, and withdrawing legitimacy from practices that persist mainly because they are familiar. De Holan and Phillips (2004) show that forgetting can be either accidental or deliberate. For AI-era organizations, deliberate forgetting matters most. They need mechanisms for retiring obsolete prompts, outdated knowledge-base entries, inherited boilerplate, and performance metrics that reward repetition over reflection.

A useful managerial question is not only ‘What should our people learn about GenAI?’ but also ‘What should our organization stop normalizing?’ Some firms, for example, still reward employees for producing large amounts of documentation rather than high-quality documentation. Others still assume that expertise must be expressed in long-form text, even when AI can produce text fluently without genuine understanding. Such assumptions can survive technology change unless unlearning is explicitly managed.

Operationally, unlearning requires visibility. Leaders need inventories of legacy routines, criteria for retiring outdated templates, and forums where employees can question long-standing practices without being treated as disruptive. This is where psychological safety becomes relevant. Edmondson (1999) shows that learning behavior depends on whether people feel able to speak up, admit mistakes, and ask for help. In the context of AI, the same logic applies to unlearning: employees must be able to challenge inherited routines and machine-generated output without fear that doing so will be read as resistance or incompetence.

Seen this way, unlearning is a governance capability. It tells the organization how to close loops, not only how to open them. Without it, AI investments tend to accumulate around old structures, resulting in partial automation layered on top of obsolete logic. With it, organizations can use AI as an occasion to renew core assumptions, roles, and routines.

A practical unlearning cycle can be described in four stages. The first is diagnosis: identifying routines that still organize work but no longer fit the new technological or institutional context. The second is suspension: temporarily withdrawing the privileged status of those routines so alternatives can be tested. The third is replacement: introducing reviewed prompts, revised templates, and new review rights that align with current tasks and risks. The fourth is reinforcement: making sure the new routine is not treated as an optional exception but as the emerging standard. This cycle is important because organizations often declare change without dismantling the mechanisms that reproduce the old routine.

Importantly, unlearning should not be interpreted as forgetting everything that came before. Many pre-AI routines contain valuable domain knowledge, legal caution, and relational wisdom. The task is selective retirement. Managers need to distinguish between routines that encode durable expertise and routines that merely reflect historical path dependence. In practice, this means that AI transformation should include routine audits, exception reviews, and decision logs that explain why some practices are being retired while others are retained.

From Hallucination to Competency Trap: When Bad Outputs Become Bad Memory

The danger becomes greater when fluent error interacts with existing capability structures. Leonard-Barton (1992) showed that organizational strengths can harden into rigidities when familiar solutions crowd out alternative ways of thinking. In the GenAI era, a similar dynamic may emerge when employees repeatedly accept machine output because it appears to match existing expectations. The result is not simply inaccuracy; it is a competency trap in which speed, convenience, and formal polish are mistaken for valid expertise. Over time, the organization becomes better at reproducing a problematic routine and less willing to reopen the assumptions embedded in it.

This is why hallucination should not be treated solely as a technical model defect. It is also an organizational design issue. Whether a hallucinated output becomes consequential depends on how the organization labels drafts, allocates review rights, records corrections, and encourages upward challenge. In units with weak verification and strong time pressure, even minor inaccuracies can sediment into slides, manuals, scripts, and standard replies. In units with stronger review norms, the same model limitations may become opportunities for better collective learning because errors are surfaced, discussed, and converted into improved guidance (Bender et al., 2021; Ji et al., 2023).

A major reason why GenAI changes organizational learning is that errors can become institutionalized before they are recognized. The hallucination problem is central here. Hallucinations occur when a generative model produces content that is fluent and plausible but unsupported, fabricated, or contextually wrong (Ji et al., 2023). In consumer contexts, this may be inconvenient. In organizations, it can be far more serious because machine output is often copied into workflows, templates, onboarding materials, or decision support documents that persist beyond the original task.

The organizational danger is not only the initial error. It is the transition from isolated mistake to repeated practice. Levitt and March (1988) noted that

organizations learn from interpretations of history, not history itself. Under GenAI, that insight becomes more urgent because machine systems can reshape those interpretations at scale. When employees repeatedly encounter polished AI-generated outputs, they may begin to treat them as authoritative patterns, especially under time pressure. The result is a competency trap: a routine appears efficient and productive, so it is reinforced even though its underlying quality is weak (March, 1991; Leonard-Barton, 1992).

The trap becomes sharper when organizations mistake convenience for capability. A team that uses GenAI to prepare client responses, summarize policy changes, or generate market analyses may initially improve throughput. Over time, however, the team may reduce its own checking behavior, lose sensitivity to nuance, and normalize outputs that are ‘good enough’ linguistically but not substantively. The organization then develops a false competence: it appears faster and more informed while actually becoming more dependent on unchecked machine mediation.

This is why hallucination risk should be treated not just as a technical concern but as a learning and memory concern. Error governance must include procedures for verifying high-impact outputs, logging recurring failure modes, tagging contested content, and tracing how flawed artifacts spread across units. In other words, organizations need memory hygiene. They must know not only what they store, but also why it is trusted and how quickly it can be corrected. This governance imperative is also consistent with emerging work on generative AI governance, which emphasizes validation, control, and adaptive oversight rather than unstructured deployment (Taeihagh, 2025).

Small-loss logic is helpful here. Sitkin (1992) argued that organizations often learn more effectively from manageable failures than from either success or catastrophic breakdowns. In AI contexts, this suggests that organizations should design controlled experiments in which outputs can be tested, challenged, and corrected before they are widely institutionalized. Pilot projects, red-team reviews, annotated prompts, and explicit exception logs all create opportunities for small losses that prevent large memory failures.

A mature GenAI learning system therefore does not aim to eliminate all mistakes in advance. It aims to prevent weak output from becoming durable organizational memory. The distinction is important. If the organization waits for perfect accuracy before experimentation, it will slow adaptation. If it ignores accuracy while accelerating adoption, it will encode poor practice. The strategic goal is disciplined experimentation with fast correction.

Risk varies by task domain. An inaccurate marketing tagline and an inaccurate compliance summary do not carry the same consequences, even if both were generated with the same interface. For this reason, organizations

need graded verification protocols. High-impact tasks should require stronger evidentiary checks, clearer ownership, and stricter archival rules than low-risk drafting tasks. Such task differentiation allows organizations to learn quickly where appropriate without treating all outputs as equally trustworthy.

Finally, hallucination risk is compounded by social dynamics. Under deadline pressure, employees may hesitate to challenge machine output that appears fluent or to question a colleague who used an approved AI system. Unless organizations explicitly legitimize review and escalation, silence can become part of the competency trap. The issue is therefore not only whether the model is wrong, but whether the organizational context makes it easy or difficult to notice and correct that wrongness.

Generative AI as an Active Organizational Actor in Memory Formation

Treating GenAI as an active organizational actor does not mean attributing intentionality or moral agency to a model. Rather, it means recognizing that the system materially participates in who remembers what, how knowledge is formatted, and which options become salient during work. A model that summarizes meetings, drafts communications, recommends next steps, or retrieves earlier examples influences attention and codification even when final authority remains human. From an organizational perspective, that influence is significant because memory is not simply stored information; it is a patterned arrangement of cues, categories, and retrieval pathways that shape future action (Walsh & Ungson, 1991).

This view also helps clarify why human-AI collaboration should be studied at the level of routines, not only at the level of individual tasks. Employees do not interact with GenAI in isolation. They interact through teams, shared repositories, prompt libraries, approval practices, and common expectations about what counts as a good output. As Seeber et al. (2020) suggest in their research agenda on machines as teammates, the central managerial challenge is to design collaboration arrangements in which the machine expands capacity without silently redefining standards in ways the organization does not notice.

Many organizations still talk about AI as if it were merely a passive tool, a repository, or a productivity layer. That framing is no longer adequate. In practice, GenAI often behaves as an active socio-technical participant in organizing. It proposes options, structures conversations, drafts narratives, sets defaults, surfaces some knowledge while obscuring other knowledge, and shapes what is likely to be copied, stored, and reused. In that sense, AI is not simply supporting memory; it is helping configure memory.

Research on AI in organizing supports this interpretation. Faraj, Pachidi, and Sayegh (2018) argue that learning algorithms reshape expertise,

occupational boundaries, and control in organizations. Jarrahi (2018) similarly suggests that AI becomes most consequential when humans rely on it as a complement in equivocal decision environments. Seeber et al. (2020) go further by proposing the idea of machines as teammates, emphasizing that AI can become a contributor to collaborative processes rather than an inert background technology. Together, these perspectives imply that organizational memory in the AI era is co-produced through human and machine interaction. Recent meta-analytic evidence also suggests that human-AI combinations do not automatically outperform either humans or AI alone, which makes the design of collaboration routines especially consequential (Vaccaro et al., 2024).

This has at least three implications. First, AI affects what becomes visible. Retrieval-augmented systems, summarizers, and assistants decide which prior documents, phrases, or categories appear salient at the moment of action. Second, AI affects what becomes repeatable. If a generated template is reused across units, it can standardize behavior quickly, sometimes faster than formal policy processes. Third, AI affects what becomes legitimate. Employees may infer that machine-generated outputs carry institutional approval simply because they are produced inside authorized systems.

Treating GenAI as an active actor does not mean anthropomorphizing it. It means acknowledging its performative effects in organizational life. Human beings still remain accountable for judgment, verification, and consequences. However, once a system shapes the production, retrieval, and circulation of knowledge, managers must analyze not only what employees know, but also how AI influences what the organization comes to treat as knowable.

This shift also changes the design of institutional memory. Traditional memory systems depended on documents, routines, role holders, and cultural scripts (Walsh & Ungson, 1991). AI adds a dynamic layer that can continuously rewrite, summarize, and reorganize those artifacts. As a result, memory is no longer only a storage question. It becomes a curation question. Which prompts are approved? Which outputs are reusable? Which summaries are tagged as verified? Which corrections feed back into future retrieval? These questions determine whether AI enriches memory or destabilizes it.

For managers, the practical takeaway is clear: GenAI should be governed as a memory-shaping teammate, not merely deployed as a neutral content generator. That means defining escalation rules, version control practices, domain-owner review rights, and acceptable use boundaries for different knowledge tasks. The more the system influences what is remembered, the more explicit those rules must become.

This perspective also has implications for accountability. If AI adoption is framed as automation alone, responsibility is often shifted downward to end users. If the system is recognized as a socio-technical participant, however, governance can be organized more realistically around model limitations, data provenance, workflow design, role clarity, and review obligations. Responsibility does not disappear; it becomes distributed across technical design and managerial design.

An additional implication concerns professional identity. In many organizations, expertise is partly defined by the ability to know, interpret, and explain. When AI drafts answers and retrieves precedents, experts may no longer act only as sources of knowledge; they increasingly act as validators, curators, and exception handlers. This does not diminish expertise. Rather, it repositions expertise around judgment and stewardship. Organizations that understand this shift are more likely to redesign roles productively instead of treating AI merely as a cost-saving substitute.

Measuring Learning Agility and Adaptive Capacity

Measurement also has a sequencing function. Early in adoption, organizations may need to privilege indicators that capture verification discipline and issue visibility rather than productivity gains. Later, once review routines mature, leaders can place greater emphasis on cycle-time reduction, cross-unit reuse, and capability renewal. This staged logic prevents organizations from demanding mature-state efficiency before the learning system has become trustworthy. It also reminds managers that KPIs are not neutral descriptors; they shape attention and can either support or distort adaptation depending on what they prioritize.

Another useful principle is triangulation. No single indicator captures learning quality in a GenAI-enabled system. A unit may show high adoption, for example, while simultaneously relying on poor verification. Another may show modest adoption but strong correction speed and high-quality documentation. Reading metrics in combination is therefore essential. Managers should examine how output quality, escalation behavior, retirement of obsolete content, and knowledge reuse interact over time rather than chasing a single headline number.

Concepts such as learning agility, adaptive capacity, and skills renewal are attractive in principle but often vague in practice. For a chapter intended to inform managers, these ideas need operational expression. The point is not to create a universal scorecard. Rather, it is to identify indicators that reveal whether the organization is learning responsibly in the presence of GenAI.

A useful measurement system should cover at least four domains:

capability renewal, memory quality, correction speed, and behavioral conditions for experimentation. Capability renewal captures whether employees are actually building new competencies. Memory quality captures whether machine-assisted content is verified before reuse. Correction speed captures how rapidly weak outputs are identified and retired. Behavioral conditions capture whether people can question AI-supported work without fear. Capability renewal is especially important because AI assistance may improve immediate task performance while still accelerating skill decay or reducing awareness of declining expertise (Macnamara et al., 2024).

Table 1 presents an indicative KPI framework that organizations can adapt by sector, task criticality, and governance maturity. The core logic is that learning should be measured not only by adoption intensity, but also by verification, retirement of outdated routines, and safe reporting of mistakes.

Construct	Illustrative KPI	What It Indicates	Example Use
Skills renewal	Reskilling completion rate	Share of targeted employees who complete role-relevant GenAI training and applied practice.	Track by function, role family, and quarter.
Learning agility	Validated AI adoption rate	Percentage of AI-assisted tasks used with documented human verification.	Differentiate low-risk from high-risk workflows.
Memory quality	Verified output reuse ratio	Proportion of reused AI-generated artifacts that have passed review before becoming durable templates.	Apply to prompts, client messages, summaries, and policy drafts.
Correction speed	Error correction cycle time	Time required to identify, review, and replace flawed machine-assisted content.	Monitor recurring failure modes and escalation delays.
Unlearning	Obsolete routine retirement rate	Number or percentage of outdated templates, prompts, or workflows removed in a given period.	Use during AI transformation milestones.
Knowledge sharing	Cross-unit knowledge reuse frequency	Extent to which reviewed artifacts are reused across teams instead of recreated locally.	Signals whether learning travels across the organization.
Psychological safety	AI issue escalation rate	Frequency with which employees report problematic outputs, prompt failures, or unsafe uses.	Low rates may indicate silence rather than quality.
Experimentation quality	Pilot-to-policy conversion rate	Share of AI experiments that become formalized practices after review and evidence collection.	Prevents ad hoc pilots from silently hardening into policy.

Table 1. Indicative KPIs for learning agility and adaptive capacity in GenAI-enabled organizations (Argote, 2013; Levitt & March, 1988; March, 1991; Walsh & Ungson, 1991; Tsang & Zahra, 2008; Edmondson, 1999; Sitkin, 1992).

KPIs should be interpreted as conversation starters rather than fixed formulas. For example, a high AI issue escalation rate may indicate poor quality in one unit but healthy speak-up behavior in another. Likewise, a high validated AI adoption rate may reflect robust routines, or it may reflect narrow task design that permits only low-risk use cases. Metrics gain meaning when they are read together and tied to task criticality.

A second measurement principle is balance. If leaders monitor only adoption, they encourage superficial use. If they monitor only errors, they discourage experimentation. Stronger systems combine adoption, verification, correction, and retirement measures so that managers can see whether the organization is becoming more capable or merely more dependent. For this reason, AI-related metrics should also reveal whether the organization is developing capabilities through a productive balance of exploration and exploitation over time (Ritala et al., 2024).

Integrating Experimentation into Performance Management

A further implication concerns the role of managers as interpreters of experimental evidence. Employees can surface anomalies and refine prompts, but line managers decide whether these signals are treated as noise, failure, or organizational learning. When managers dismiss correction activity as inefficiency, employees infer that visible certainty is safer than careful doubt. When managers recognize disciplined experimentation as a contribution to memory quality, they send the opposite signal: that surfacing weak spots is part of capable performance. In this way, performance systems do not merely evaluate learning; they authorize or suppress it.

HR systems can reinforce this alignment by embedding developmental criteria into appraisal templates, leadership expectations, and internal mobility decisions. Teams that document reusable insights, mentor others in safe AI use, and retire low-value routines should be recognized for strengthening organizational capability, even when such work does not immediately maximize short-term throughput. A learning-oriented HR architecture therefore treats adaptive behavior as a visible component of performance rather than as invisible maintenance work.

Even well-designed learning routines fail when performance systems punish the very behaviors they require. This is one of the most practical gaps in many organizational AI programs. Leaders encourage experimentation, pilot use cases, and rapid learning, yet employees remain embedded in appraisal systems that reward flawless execution, short-term throughput, and low visible error rates. Under such conditions, people either avoid experimentation or hide the problems they encounter while experimenting.

This misalignment matters because learning from AI is inherently iterative. Employees have to compare outputs, test prompts, surface anomalies, and refine workflows. If every deviation from established practice is treated as inefficiency, then the organization creates a climate in which adaptive learning is rhetorically encouraged but behaviorally discouraged. Edmondson's (1999) work on psychological safety is directly relevant here: people are more likely to engage in learning behaviors when they believe that speaking up, asking questions, and admitting mistakes will not trigger interpersonal punishment.

Performance management in the age of GenAI therefore needs at least three adjustments. First, organizations should distinguish negligence from intelligent experimentation. Not every failed AI-assisted output is evidence of poor performance. In many cases, it is evidence that the organization is still learning task boundaries, data constraints, and review requirements. Second, organizations should evaluate learning behaviors in addition to outcome metrics. Employees who document prompt failures, improve verification routines, and share corrected templates contribute to institutional learning even when the first attempt falls short. Third, formal appraisal systems should recognize contribution to memory quality, not just task completion volume.

This does not imply tolerating careless use. High-risk tasks still need strict controls, expert review, and accountability. The point is more precise: organizations should not design systems in which employees are penalized for surfacing uncertainty early. A healthy design is one in which low-risk experimentation is welcomed, high-risk use is tightly governed, and evidence from both flows into better routines.

One practical approach is to create protected learning zones. These may include sandbox environments, pilot charters, temporary review committees, or staged release processes in which teams can test AI-supported practices before they become standard. Another is to integrate learning metrics into managerial dashboards so that leaders can see whether teams are reporting issues, retiring outdated routines, and improving output verification rates. When these indicators appear in formal review processes, experimentation becomes institutionally legitimate rather than an off-the-books activity.

In this sense, performance management becomes part of organizational memory design. It signals what kinds of behavior are worthy of repetition. If the system rewards only speed, then employees learn to prioritize speed. If it rewards verified learning, safe escalation, and disciplined improvement, then those behaviors are more likely to become durable routines.

Managers should also pay attention to evaluation timing. In many organizations, AI-enabled experimentation produces short-term inefficiencies before it yields stable improvements. Early pilots may require more review,

slower sign-off, and additional peer consultation. If managers evaluate teams too early against mature-state productivity targets, they create pressure to bypass learning safeguards. Review windows and expectations should therefore be calibrated to the stage of adoption.

Finally, performance integration should not stop at individual appraisal. Team leaders, functional heads, and senior sponsors also need accountability for the quality of the learning environment they create. Whether employees can question AI-supported work, whether error reports are acted on, and whether obsolete templates are actually retired are managerial outcomes, not merely employee behaviors.

A Managerial Roadmap for AI-Ready Learning Systems

Building an organizational learning system for the GenAI era does not begin with model selection. It begins with governance choices about knowledge, verification, and incentives. A practical roadmap can be organized into four moves.

Figure 1. Four-step managerial roadmap for AI-ready learning systems (*Argote, 2013; Nonaka, 1994; Walsh & Ungson, 1991; Tsang & Zahra, 2008; Raisch & Krakowski, 2021; Seeber et al., 2020*).

1. Map AI Memory Touchpoints Identify where GenAI already shapes summaries, prompts, onboarding materials, and reusable outputs.	2. Build Verification Pathways Separate draft content from validated knowledge and assign clear review rights for reusable artifacts.
3. Retire Obsolete Routines Create unlearning workflows, ownership rules, and archival signals so legacy guidance does not persist.	4. Renew Human Capability Invest in judgment, escalation, and override skills—not only tool access or technical familiarity.

1. Map AI memory touchpoints. Organizations should identify where GenAI already shapes memory formation, including summaries, meeting recaps, shared prompts, onboarding materials, and reusable client-facing artifacts. Once these touchpoints are visible, leaders can distinguish low-risk knowledge tasks from high-impact tasks and assign appropriate review rights.

2. Build verification pathways. Firms should maintain reviewed prompt libraries, domain-owner approvals for reusable artifacts, and clear labels that distinguish draft outputs from validated knowledge. This is especially important in sectors where legal exposure, regulation, professional norms, or customer vulnerability create narrow tolerance for error.

3. Retire obsolete routines. Human-verified templates can become obsolete just as quickly as AI-generated ones. Memory systems therefore need unlearning workflows, ownership rules, and archival signals that distinguish

active guidance from legacy material. Without these distinctions, old and new practices become entangled in ways that confuse employees and weaken adaptation.

4. Renew human capability. Leaders should invest not only in technical training, but also in judgment training: how to question AI output, how to identify failure modes, and how to decide when human expertise should override machine fluency. These are not peripheral skills; they are part of the new core of organizational learning.

This roadmap suggests that GenAI capability is not reducible to adoption metrics. It is better understood as the organization's capacity to produce trustworthy knowledge under conditions of speed, ambiguity, and machine mediation. The stronger the connection between learning, unlearning, verification, and performance alignment, the more likely the organization is to convert AI use into durable capability.

Conclusion

For scholars, this perspective suggests that future research should not ask only whether AI improves performance, but under what governance, memory, and incentive conditions AI contributes to resilient organizational learning. For practitioners, the message is equally direct: the competitive issue is not who deploys GenAI first, but who can turn machine-mediated experimentation into reliable institutional capability. Organizations that combine verification, unlearning, psychological safety, and capability renewal are more likely to build durable advantage than those that rely on enthusiasm and adoption counts alone.

Generative AI does not eliminate the classic challenges of organizational learning; it intensifies them. Organizations still have to create, retain, transfer, and apply knowledge, but they must now do so in environments where content can be generated at scale, errors can look persuasive, and memory can be shaped by socio-technical systems that act inside everyday work.

The chapter has argued that the central task is not merely to accelerate learning, but to build high-quality learning. That requires deliberate unlearning, protection against competency traps, explicit treatment of GenAI as a memory-shaping actor, measurable indicators of learning agility, and performance systems that legitimize disciplined experimentation. Organizations that succeed in these areas will not simply use AI more often. They will develop more reliable memory, faster correction, and stronger adaptive capacity.

In that sense, the future of learning in organizations is not a contest between human and machine intelligence. It is a question of how institutions

design the relationship between them so that speed does not outrun judgment and novelty does not erode memory quality.

Two practical implications follow. First, leaders should treat memory design as a core part of AI strategy. Decisions about where AI outputs can be reused, who validates them, how corrections are logged, and when legacy content expires are not administrative details; they determine whether the organization accumulates trustworthy knowledge or scalable confusion. Second, organizations should distinguish between visible productivity and durable capability. A unit that produces more content with AI is not necessarily learning well. Durable capability is present only when speed is paired with verification, routine retirement, and a willingness to revise what the organization takes for granted.

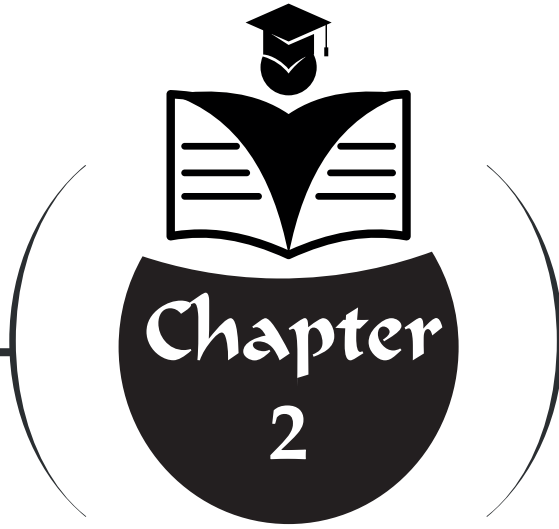
Ultimately, organizational learning in the age of GenAI is less about absorbing a new tool than about redesigning the social and managerial conditions under which knowledge becomes credible, reusable, and adaptable. The organizations most likely to benefit from AI are those that convert machine fluency into humanly governed learning systems. They build psychological safety around questioning, create explicit pathways for correction, invest in judgment alongside technical skills, and make unlearning a visible part of responsible performance. In that sense, the future of organizational capability depends not only on what AI can generate, but on what organizations are prepared to learn, unlearn, and remember.

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INSTITUTIONAL MEMORY,
ADAPTIVE CAPACITY, AND
ORGANIZATIONAL RESILIENCE IN
AI-ENABLED ORGANIZATIONS

Introduction

Institutional memory has become newly important in the age of artificial intelligence. As organizations deploy generative, predictive, and knowledge-retrieval systems across administrative, professional, and operational work, they increasingly rely on digital systems to preserve precedents, surface lessons, and guide action. Yet the central managerial question is not whether more information can be stored. It is whether memory can support coordinated action when organizations face ambiguity, disruption, turnover, and accelerating technological change.

Classic management research has long treated organizational memory as a foundational element of learning and continuity. Organizations remember through people, routines, stories, role structures, archives, and artifacts rather than through individual cognition alone (Walsh & Ungson, 1991; Argote, 2013). This memory matters because it shapes interpretation, coordination, and performance. What an organization retrieves from its past influences how it categorizes a novel problem, whom it treats as an expert, which response becomes legitimate, and how quickly it can move from confusion to action. Memory is therefore not a passive storehouse. It is a distributed infrastructure of attention and judgment.

In AI-enabled organizations, this infrastructure changes qualitatively. Digital tools do not merely preserve what already exists; they reorganize access, compress context, privilege certain traces over others, and increasingly generate synthetic summaries that can begin to function as organizational precedent. Recent work on AI in organizations shows that intelligent systems alter managerial work, information flows, and the distribution of expertise (Lee et al., 2023; Bankins et al., 2024). At the same time, research on human-centered AI warns that apparently efficient systems can weaken accountability and obscure the conditions under which outputs are produced (Bryson & Theodorou, 2019; Taylor et al., 2024). In other words, AI changes not only decision support but also what is remembered, how it is retrieved, and whose interpretation becomes durable.

This chapter argues that institutional memory is best understood as a resilience capability in AI-enabled organizations. Resilience is not simply resistance to shock. It is the capacity to anticipate threats, cope effectively under strain, and adapt after disruption (Duchek, 2020). Institutional memory contributes to each of these tasks. It provides access to prior failures, near misses, exception handling, role relationships, and local improvisations that help organizations anticipate vulnerabilities. Under pressure, it supports coordination by making verified knowledge retrievable beyond a single expert

or unit. After disruption, it preserves what was learned so that adaptation is not lost when attention shifts or personnel change.

However, memory becomes a resilience resource only under specific conditions. It must be curated rather than merely accumulated, distributed rather than hoarded, and verified rather than blindly reused. AI intensifies all three requirements. Generative systems can improve retrieval and reduce dependence on a few experts, but they can also amplify outdated routines, flatten crucial contextual nuance, and create what this chapter terms synthetic memory drift: the gradual normalization of machine-generated reconstructions as if they were faithful representations of prior organizational experience. The result can be brittle continuity - a situation in which organizations appear well documented yet remain poorly prepared for disruption.

The chapter proceeds in seven steps. First, it revisits institutional memory as a multidimensional organizational resource. Second, it shows how memory fails through erosion, fragmentation, and synthetic drift. Third, it connects memory quality to adaptive capacity and resilience. Fourth, it examines AI as a co-curator and co-shaper of memory rather than a neutral repository. Fifth, it proposes a resilient memory architecture for AI-enabled organizations. Sixth, it offers a practical dashboard of indicators that managers can use to monitor memory quality and resilience readiness. The chapter concludes by arguing that, in the AI era, resilient organizations are distinguished not by how much they store but by how deliberately they preserve, interpret, and renew institutional memory.

Institutional Memory in AI-Enabled Organizations

Organizational memory research emerged from a basic insight: organizations retain knowledge beyond the lives, perceptions, and intentions of individual members. Walsh and Ungson (1991) conceptualized organizational memory as information stored in a set of retention bins, including individuals, culture, transformations, structures, ecology, and external archives. Subsequent work extended this idea by showing that memory is created, retained, and transferred through social interaction, routines, and knowledge systems (Argote, 2013; Argote et al., 2000). Linde (2008) further demonstrated that narratives and stories are not peripheral to memory but central to how institutions preserve identity and interpret the meaning of past action.

Three points from this literature remain especially important for contemporary organizations. First, institutional memory is distributed. Critical knowledge lives partly in formal repositories, but also in expert networks, tacit know-how, and role relationships. Nonaka and Takeuchi (1995) and Polanyi (1966) remind us that not all knowledge can be fully

codified. An organization may have extensive documentation and still lose crucial competence if it cannot locate who knows what, why an exception was made, or how a rule is adapted in practice. Research on transactive memory systems similarly shows that collective performance depends not only on possessing knowledge but on knowing where expertise resides and how it can be mobilized (Ren & Argote, 2011).

Second, memory is selective. Organizations do not preserve everything. They filter, prioritize, and stabilize some experiences while allowing others to fade. Levitt and March (1988) showed that routines are shaped by interpretations of experience, not raw experience itself. This means that organizational memory always contains judgments about relevance and legitimacy. Certain incidents become templates; others remain isolated episodes. Some lessons are institutionalized through forms, checklists, and workflows; others persist only as local lore. This selectivity makes memory useful, but it also introduces risk when the preserved past becomes unrepresentative of current conditions.

Third, memory is performative. It does not simply describe what happened previously; it influences what will happen next. Moorman and Miner (1997) demonstrated that organizational memory can support performance and creativity when prior knowledge is accessible and usable. Yet the same logic suggests that memory can also constrain action when it locks organizations into stale assumptions. Berger and Udell's (2004) institutional memory hypothesis, though developed in banking, offers a broader organizational lesson: when experienced actors leave and memory thins out, the quality of judgment deteriorates, especially under changing conditions.

These three characteristics - distribution, selectivity, and performativity - acquire new importance in AI-enabled organizations. Intelligent systems interact with each dimension. They can aggregate distributed traces from multiple repositories, making knowledge more portable across teams and hierarchy levels. They can also intensify selectivity by privileging what is machine-readable, frequently accessed, or easily summarized. Finally, they reshape performativity because AI outputs can appear more authoritative than informal human recollections, even when they rest on weak or outdated sources.

This shift helps explain why AI should not be treated only as a search accelerator. It becomes part of the institutional memory infrastructure itself. A retrieval system that prioritizes the most complete document over the most recent incident, or a summarization system that suppresses exceptions in favor of typical patterns, is already shaping what counts as organizational memory. The issue is therefore not whether memory becomes digital; most organizational memory already is. The issue is whether AI-enabled memory

architectures preserve contextual depth, traceability, and interpretive plurality rather than reducing memory to polished but context-thin output.

Recent case-based research supports this concern. Nagayoshi and Nakamura (2024) show that digital systems can strengthen memory and learning from failure, but only when organizations connect computer usage to reflective review and knowledge-sharing practices rather than assuming that storage alone creates learning. Ritala et al. (2024) similarly argue that industrial AI capabilities develop through organizational learning processes, not through technology acquisition in isolation. These findings imply that institutional memory remains social and socio-technical even when AI becomes deeply embedded. The problem is never just preservation; it is preservation plus interpretation plus mobilization.

When Memory Fails: Erosion, Fragmentation, and Synthetic Drift

If institutional memory can support continuity and resilience, it can also fail in systematic ways. Three failure modes are especially relevant in the AI era: erosion, fragmentation, and synthetic drift.

Memory erosion occurs when critical knowledge disappears faster than it is renewed. Turnover, retirement, restructuring, outsourcing, and platform migration can all thin out organizational memory. Some erosion is visible, such as when a veteran expert leaves. More dangerous forms are gradual. Workarounds, exception criteria, and subtle warning signs are often carried through habit rather than written doctrine. When personnel change or tasks are standardized, organizations may discover that they have preserved procedures but lost judgment. Research on organizational forgetting in crisis settings reinforces this point by showing that institutions often lose knowledge not because no one documented the past, but because attention moved on, repositories were not maintained, or crisis lessons were never integrated into ordinary work (Broekema, 2025).

Fragmentation occurs when knowledge survives locally but not institutionally. A plant, branch, professional community, or digital team may possess highly refined experience, yet the organization as a whole cannot retrieve it when conditions shift. Fragmentation is especially common in complex organizations that operate across functions, regions, and technical systems. It produces a misleading sense of competence: expertise exists, but it is not visible or mobilizable across boundaries. Coffey and Hoffman (2003) note that preserving institutional memory requires deliberate knowledge modeling because raw documentation rarely captures the conceptual structure that makes expertise reusable. Fragmentation therefore becomes a resilience problem. During disruption, organizations need access not only to

official policy but to situated knowledge about local dependencies, informal coordination paths, and prior anomalies.

Synthetic drift is more specific to the current technological moment. It refers to a condition in which AI-generated reconstructions, summaries, or recommendations gradually begin to stand in for verified historical memory. Generative systems are particularly useful because they convert messy archives into readable syntheses. Yet the same convenience can suppress uncertainty, omit minority experiences, and normalize incorrect or outdated interpretations. A machine-produced summary may appear more legible and therefore more reusable than a messy but accurate incident record. Over time, this can shift organizational memory from traceable precedent toward synthetic precedent.

Synthetic drift differs from simple hallucination. A hallucination is an immediate output error. Synthetic drift is cumulative and organizational. It occurs when repeated AI-assisted use changes what the organization treats as remembered truth. This can happen even when individual outputs are plausible. For example, if a system repeatedly summarizes prior disruptions by foregrounding dominant response patterns while excluding unusual but important exceptions, it may train managers to remember the past as more stable and homogeneous than it was. In resilience terms, this weakens sensitivity to weak signals and edge cases.

These risks do not imply that digital systems should be distrusted wholesale. They imply that memory quality must be governed. Human-centered AI scholarship is useful here because it stresses transparency, traceability, and the continued importance of human judgment in system design and use (Bryson & Theodorou, 2019; Taylor et al., 2024). In the context of institutional memory, the lesson is straightforward: organizations should distinguish between archived evidence, interpreted memory, and AI-generated synthesis. When those categories blur, resilience becomes fragile because teams can no longer tell whether they are drawing on grounded experience or on a convenient reconstruction of it.

This distinction matters most under pressure. Resilience failures often occur not because organizations lack any memory, but because the memory available at the point of action is incomplete, decontextualized, or overly sanitized. Near misses are especially vulnerable to erasure because they generate less formal documentation than major incidents. Yet such cases are often the richest source of adaptive knowledge. A memory system that retains success stories but loses anomalous warning signs may look comprehensive while quietly undermining adaptive capacity.

From Institutional Memory to Adaptive Capacity and Resilience

Resilience research provides a useful vocabulary for understanding why memory matters beyond efficiency. Duchek (2020) conceptualizes organizational resilience as a meta-capability composed of anticipation, coping, and adaptation. This framework clarifies how institutional memory contributes to resilient performance.

Memory supports anticipation by making prior disruptions, precursors, and near misses visible before a crisis fully unfolds. Anticipation is not prediction in a narrow statistical sense. It is the organizational ability to notice patterns, interpret anomalies, and imagine plausible consequences. Historical incident records, annotated after-action reviews, and preserved narratives about difficult trade-offs help organizations recognize how seemingly minor signals may interact. Weick, Sutcliffe, and Obstfeld (1999) make a related argument in their work on collective mindfulness: high-reliability organizations remain attentive to failure because they resist oversimplification and stay sensitive to operational detail. Institutional memory enables this attentiveness when it preserves heterogeneity rather than merely codifying standard cases.

Memory supports coping by reducing coordination latency during disruption. Under time pressure, resilient organizations rarely invent everything from scratch. They retrieve templates, contacts, escalation pathways, and workarounds that enable faster action. However, what matters is not the existence of a static playbook alone. Effective coping depends on memory that is both accessible and interpretable. A procedure manual that no one trusts, or a knowledge base that cannot surface context-specific exceptions, offers little resilience value. Distributed memory structures - such as expert maps, cross-functional incident logs, and preserved narratives of prior improvisation - help teams coordinate when formal roles alone are insufficient.

Memory supports adaptation after disruption by ensuring that lessons survive beyond the immediate moment of attention. Many organizations conduct postmortems or after-action reviews but fail to reintegrate lessons into routines, training, and system design. The result is episodic learning without durable adaptation. Institutional memory turns temporary insight into enduring capability when it captures not only what was decided, but why it was decided, what uncertainties remained, and what signals were missed. This is why resilience and memory should be considered jointly. Adaptation without memory dissipates; memory without adaptation ossifies.

In AI-enabled organizations, the relationship becomes even more consequential. Predictive systems can support anticipation, retrieval systems can support coping, and generative systems can help codify learning after

disruption. But these advantages are conditional. If the underlying memory base is partial, biased, or stale, AI can accelerate weak judgment rather than strengthen resilient action. Bankins et al. (2024) emphasize that AI affects organizational behavior across multiple levels, including perception of expertise, distribution of authority, and the interpretation of work. This means that memory quality indirectly shapes how AI influences resilience.

Adaptive capacity therefore rests on more than information abundance. It depends on the organization's ability to move between retention and revision. Some memory must be stabilized so that recurring coordination can be trusted. Other memory must remain contestable so that anomalous events are not forced into familiar categories. A resilient organization does not preserve the past indiscriminately. It preserves enough traceable experience to act coherently, while keeping enough interpretive openness to revise assumptions when conditions change.

This tension also explains why institutional memory can become a source of fragility. If memory is preserved as unquestioned precedent, the organization may become efficient but brittle. If it is treated as endlessly revisable, the organization may lose continuity and fail to coordinate under stress. Resilience requires a managed balance: memory must be stable enough to support rapid mobilization and flexible enough to support re-interpretation. That balance is increasingly difficult, and increasingly important, in contexts where AI systems intensify the speed and scale of retrieval.

AI as Co-Curator and Co-Shaper of Institutional Memory

Traditional discussions often describe information technology as an aid to storage, communication, or decision support. That description is now too narrow. In many organizations, AI systems act as co-curators of institutional memory. They influence which documents are retrieved, which incidents are summarized, which patterns appear salient, and which interpretations become easier to circulate. In practice, this means that AI participates in the social construction of memory even when it lacks formal authority.

Three mechanisms are especially important. First, AI systems re-rank memory. Search, recommendation, and retrieval tools make some traces more visible than others. What appears on the first screen, what is summarized as representative, and what is omitted as noise all affect the remembered organization. Second, AI systems compress memory. Generative tools turn long records into concise output. Compression is valuable, but it can also remove dissent, uncertainty, and exception logic - exactly the contextual features that matter most during crises and complex adaptation. Third, AI systems standardize memory expression. When many employees rely on the same assistant to draft reports or summarize

past decisions, organizational memory may become stylistically coherent while substantively thinner.

This is why institutional memory in AI-enabled organizations should be treated as a socio-technical achievement rather than a technical artifact. Lee et al. (2023) show that AI implementation challenges often stem from inscrutability, data dependency, and integration difficulty. Applied to memory, these challenges mean that organizations must ask not only whether AI can retrieve information, but also how source quality, provenance, and context are preserved. Human-centered AI scholarship adds a normative layer by emphasizing explainability, contestability, and accountability (Bryson & Theodorou, 2019; Taylor et al., 2024). These principles matter for institutional memory because organizations need to know whether a retrieved recommendation reflects a verified rule, a localized workaround, or a probabilistic synthesis.

The role of AI as a co-shaper of memory also affects identity and legitimacy. Linde (2008) shows that institutions remember themselves through narrative. If AI systems increasingly summarize organizational history, produce onboarding narratives, or draft strategic retrospectives, they may influence how the organization defines its own continuity. This can be useful when firms need to integrate dispersed knowledge, especially after mergers, platform migrations, or rapid scaling. But it also creates a subtle governance challenge: who reviews the memory being consolidated, and which voices become canonical?

A useful managerial principle is to treat AI outputs as memory proposals rather than memory itself. This distinction preserves the benefits of speed and synthesis while avoiding undue epistemic closure. AI can suggest precedent, connect similar cases, surface forgotten documents, and highlight recurrent problem patterns. Human actors, however, should remain responsible for validating critical interpretations, preserving dissenting cases, and maintaining traceability to original sources. In effect, organizations need memory stewardship rather than mere automation.

Ritala et al. (2024) underline that AI capabilities develop through organizational learning processes. The same insight applies here: resilient institutional memory emerges when organizations learn how to work with AI as a participant in knowledge processes without allowing it to become an unexamined author of organizational truth. The goal is not to keep AI outside memory work. The goal is to embed AI within verification-rich arrangements that protect context, plurality, and accountability.

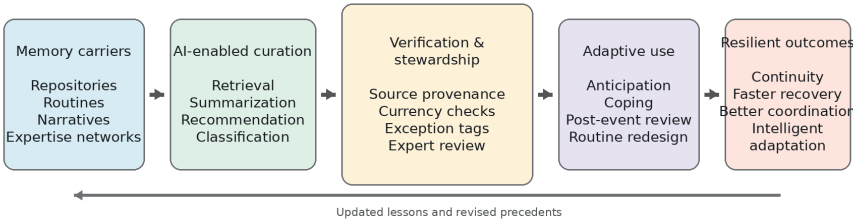
A Resilient Memory Architecture for AI-Enabled Organizations

If institutional memory is to function as a resilience capability, organizations need more than repositories. They need a memory architecture that links retention, retrieval, interpretation, and revision. Figure 1 presents a practical way of thinking about such an architecture.

At the left side of the architecture are the core memory carriers: repositories, routines, narratives, and expertise networks. Repositories include incident logs, policy archives, technical documents, customer records, and after-action reviews. Routines include escalation paths, meeting rhythms, and embedded process rules. Narratives preserve meaning, identity, and context that formal repositories often omit. Expertise networks capture who knows what and who has handled similar exceptions before. Each carrier contributes differently. Repositories improve persistence, routines improve coordination, narratives improve interpretive depth, and expertise networks improve mobilization.

At the center lies the AI-enabled curation layer. Here, retrieval systems, summarization tools, recommendation engines, and classification models help organizations make memory usable at scale. This layer adds speed and accessibility, especially in distributed organizations. Yet it must be surrounded by a verification layer that includes source provenance, currency checks, exception tagging, human review protocols, and escalation rules for high-stakes use. Without this layer, AI-assisted curation can collapse into synthetic drift.

Figure 1. A resilient memory architecture for AI-enabled organizations. Based on Walsh and Ungson (1991), Coffey and Hoffman (2003), Argote (2013), Ducheck (2020), and Lee et al. (2023).



At the right side lies the adaptation loop. Memory should feed anticipation, coordinated response, post-event review, and routine redesign. In resilient organizations, the loop does not end once an incident is closed. Lessons are evaluated, contradictions are retained rather than erased, and new knowledge is routed back into repositories, narratives, and expertise maps. This is how memory becomes adaptive capacity rather than static inheritance.

The architecture also has a governance dimension. Ownership of memory quality cannot be left to IT alone. Operations leaders, HR, knowledge managers, risk owners, and frontline experts each play a role. HR is especially important where resilience depends on role transitions, onboarding, expert succession, and the preservation of tacit know-how. Risk and compliance functions are important where memory influences safety-critical or legally consequential decisions. Cross-functional stewardship helps prevent the false assumption that memory problems can be solved through technology procurement.

A resilient memory architecture therefore depends on five design principles. First, preserve provenance so that users can trace outputs back to original sources. Second, preserve exceptions rather than only dominant cases. Third, combine codified memory with expert access so that tacit knowledge remains reachable. Fourth, review memory quality after disruptions, not just system uptime. Fifth, distinguish archival retention from operational retrieval: what is stored for record purposes is not always what should guide present action. Together, these principles increase the probability that institutional memory will remain usable under uncertainty rather than merely abundant in normal times.

Stress-Testing Memory Before the Next Disruption

Most organizations discover weaknesses in institutional memory only after a disruption, audit failure, or painful transition. A more resilient approach is to stress-test memory before the next crisis. In high-reliability and resilience-oriented settings, preparedness depends not only on technical redundancy but also on whether knowledge can be found, interpreted, and used under pressure (Weick et al., 1999; Ducheck, 2020). Memory stress testing translates this logic into managerial practice by asking whether the organization's memory architecture remains usable when time is compressed, expertise is unavailable, and routines no longer fit neatly.

Memory stress testing should begin with scenario-based retrieval exercises. Instead of asking whether repositories exist, managers can ask whether teams can recover current, traceable guidance for a realistic disruption within a short time window. For example, what happens if a frontline supervisor, an AI assistant, and a risk manager each search for the same precedent during a disruption? Do they retrieve the same guidance, or do they surface different and conflicting memories? These exercises reveal whether institutional memory is coherent enough to support collective action or whether it fragments across roles and interfaces.

A second form of stress testing focuses on edge cases. Organizations are often well prepared for expected disruptions but weakly prepared for combinations of failure. Resilience engineering research shows that socio-

technical risk often emerges from interaction effects rather than isolated incidents (Patriarca et al., 2018; Luther et al., 2023). Memory systems should therefore be tested against compound scenarios involving turnover, platform failure, regulatory change, supplier disruption, or conflicting customer obligations. Such exercises help expose whether rare but consequential knowledge has been preserved or silently lost.

A third form of stress testing concerns provenance and accountability. AI-enabled memory systems should be challenged with questions that require source tracing: Which original case supports this recommendation? What has changed since that case occurred? Was the retrieved guidance generated from a policy, a local workaround, or a synthetic summary? If the organization cannot answer these questions quickly, it may have a memory system that is efficient for routine search but unsafe for high-stakes use. Governance scholarship is useful here because it emphasizes that complex organizations need clear responsibility for contested knowledge, not merely distributed access to it (Vakkuri et al., 2021).

Stress testing also has a developmental function. It creates opportunities for latent expertise to become visible. During simulation, managers often discover that certain employees carry critical contextual knowledge not reflected in documents or formal roles. This insight should feed succession planning, onboarding design, and repository redesign. In that sense, stress testing is not just an audit of memory; it is a method for renewing memory by revealing what should be captured, linked, or retired.

A practical stress-testing routine can be built around four recurring questions. First, can we retrieve relevant knowledge fast enough under pressure? Second, can we verify where that knowledge came from? Third, do we preserve the exceptions and ambiguities that matter in unusual cases? Fourth, do lessons from rehearsal feed back into repositories, prompts, and role-based guidance? Organizations that revisit these questions regularly are more likely to convert institutional memory into adaptive capacity rather than leaving it as an untested assumption.

A Managerial Dashboard for Memory Quality and Resilience Readiness

For many organizations, institutional memory remains rhetorically valued but managerially invisible. It is discussed after turnover, incidents, or audits, yet rarely translated into operational indicators. Table 1 proposes a practical dashboard that links memory quality to resilience readiness.

The first group of indicators concerns retention quality. Managers need to know whether critical process knowledge, exception histories, and expert

know-how are actually being preserved rather than assumed to exist. Useful indicators include the proportion of mission-critical roles with documented successor notes, the share of high-risk processes with updated exception logs, and the percentage of after-action reviews converted into searchable lessons. These indicators shift attention from generic documentation volume to strategically relevant retention.

Table 1. Illustrative indicators for institutional memory quality and resilience readiness.
Based on Argote (2013), Coffey and Hoffman (2003), Ducheck (2020), Lee et al. (2023), and Nagayoshi and Nakamura (2024).

Dimension	Illustrative indicator	Managerial use
Retention quality	% of mission-critical roles with current successor notes and annotated handover files	Shows exposure to turnover and hidden knowledge concentration
Exception memory	% of high-risk processes with updated exception logs and near-miss cases	Preserves edge conditions rather than only standard cases
Retrieval quality	Median time to locate verified guidance during drills or incident simulations	Tests whether memory is operationally usable under pressure
Traceability	% of AI-generated memory outputs that include source links, dates, and document version markers	Reduces synthetic drift and improves auditability
Validation quality	% of high-stakes AI summaries reviewed by a domain expert before operational use	Protects contextual accuracy in consequential decisions
Renewal speed	Days from incident closure to repository update, prompt revision, or playbook change	Measures whether memory is being refreshed after disruption
Cross-unit transfer	% of lessons communicated beyond the originating unit within a defined period	Converts local memory into organization-wide adaptive capacity

The second group concerns retrieval quality. A large archive can coexist with poor operational memory if staff cannot locate the right knowledge under pressure. Retrieval quality can be assessed through metrics such as median time-to-locate verified guidance during drills, search success rates for incident-related queries, and the proportion of AI-generated responses that include traceable source links. These metrics matter because resilience depends on usable memory at the moment of action, not just archival completeness.

The third group concerns interpretive quality. Memory becomes dangerous when information is accessible but misleading. Here organizations can track the percentage of AI summaries flagged for missing context, the frequency with which exception cases are accessed in scenario exercises, and the proportion of critical outputs that receive expert validation before operational use. Such indicators help reveal whether the organization is preserving nuance or flattening it.

The final group concerns adaptive renewal. Resilient organizations update memory after disruptions rather than freezing it. Managers can therefore monitor cycle time from incident closure to repository update, cross-unit transfer of lessons, and the retirement of obsolete playbooks or templates. These indicators show whether institutional memory is alive enough to support adaptation.

The dashboard should not be used as a bureaucratic scorecard detached from work. Its purpose is to make invisible memory work governable. Used well, it helps leaders identify where resilience is being undermined by stale documentation, inaccessible expertise, weak source traceability, or delayed learning integration.

Managerial Implications

Managers seeking to strengthen institutional memory and resilience in AI-enabled organizations can begin with five practical priorities:

1. Map critical memory dependencies. Identify which roles, routines, repositories, and expert relationships are essential for maintaining continuity during disruption. Memory risks are often concentrated in a small number of people, files, or informal coordination channels.

2. Separate archival abundance from operational usefulness. An organization may store vast quantities of information while lacking reliable retrieval under pressure. Managers should test whether staff can quickly access current, context-rich guidance in realistic drills rather than assuming that documentation equals readiness.

3. Govern AI-generated memory artifacts. Summaries, recommendations, and retrieved precedents should carry provenance, date markers, and escalation cues. High-stakes memory outputs should be reviewable back to source documents and not treated as self-validating just because they are fluent.

4. Preserve exceptions and near misses. Standard cases are easier to codify, but resilient adaptation often depends on remembering anomalies, boundary conditions, and improvised workarounds. These should be tagged and retained rather than cleaned away as noise.

5. Institutionalize post-disruption memory renewal. After-action review should not end with discussion. Lessons need ownership, repository updates, role-based communication, and follow-up checks to ensure that revised memory actually enters routine work.

Taken together, these priorities reframe institutional memory as an active managerial domain. The objective is not to eliminate uncertainty or

automate judgment away. It is to create conditions in which organizations can remember accurately enough, distribute knowledge broadly enough, and revise precedent quickly enough to remain resilient when conditions change.

Boundary Conditions and Future Research

The arguments developed in this chapter are broadly relevant, but they are unlikely to apply in identical ways across all organizational settings. Institutional memory has different stakes and forms in highly regulated sectors, project-based firms, public organizations, and platform-mediated service systems. In safety-critical environments such as healthcare, energy, transportation, and infrastructure, the costs of synthetic drift or weak provenance are especially high because memory failures can directly affect public safety, compliance, and service continuity. In less regulated but highly dynamic settings, such as digital services or creative industries, the greater risk may be excessive standardization: AI-assisted memory systems can make organizations efficient while quietly narrowing interpretive variety.

Organizational size also matters. Large organizations often struggle with fragmentation, competing repositories, and cross-unit transfer. Smaller organizations may experience the opposite problem: memory is highly concentrated in a few individuals, making continuity vulnerable to turnover. Both conditions require governance, but the design priorities differ. Large firms need memory integration and stewardship across boundaries, whereas smaller firms often need deliberate codification and succession-oriented capture of tacit know-how.

A further boundary condition concerns institutional plurality. Hybrid and mission-driven organizations frequently work under multiple logics, such as efficiency, public value, professional standards, and accountability (Vakkuri et al., 2021). In these contexts, institutional memory is not just a technical problem of retention. It is also a political problem of whose interpretation is preserved and whose experience becomes canonical. AI-assisted curation can simplify such plurality too aggressively unless organizations preserve contested cases, dissenting accounts, and alternative rationales.

These boundary conditions suggest several directions for future research. First, more empirical work is needed on how AI-assisted retrieval changes the reliability of institutional memory under disruption rather than in routine contexts alone. Second, future studies could examine which governance mechanisms most effectively protect memory provenance and contextual richness when generative systems are widely used. Third, comparative research could explore whether organizations with stronger narrative and expert-network memory become more resilient than those relying primarily on formal repositories. Finally, the relationship between institutional memory

and sustainability deserves closer attention. Organizations facing climate, supply-chain, and social disruptions need memory systems that preserve lessons over long time horizons while still allowing timely adaptation.

Conclusion

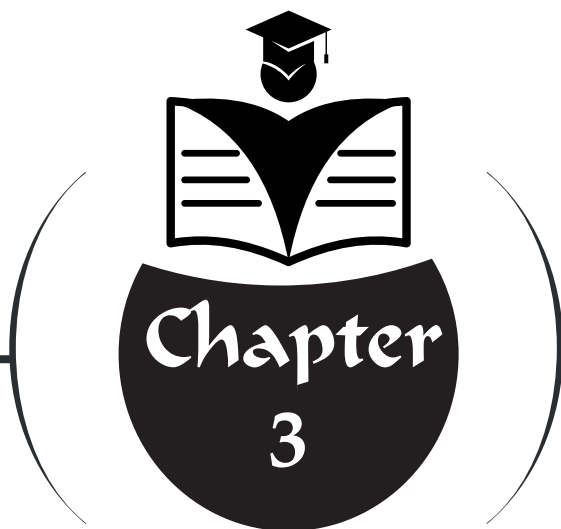
Institutional memory is often discussed as a background organizational asset, something valuable but largely invisible until it fails. In the age of AI, that view is no longer sufficient. Memory is becoming more digital, more searchable, more synthesizable, and, paradoxically, more vulnerable to distortion. As organizations rely on AI to surface precedent, summarize experience, and guide coordinated action, they need to treat memory not as passive accumulation but as a governed resilience capability.

This chapter has argued that institutional memory supports adaptive capacity by improving anticipation, coordination, and post-disruption learning. At the same time, it has shown that memory can be weakened by erosion, fragmentation, and synthetic drift, especially when AI-generated reconstructions begin to substitute for verified organizational experience. The solution is not to slow technological adoption, but to design memory architectures that preserve provenance, context, plurality, and revision. When organizations do so, memory becomes more than a record of what they once knew. It becomes a strategic resource for coping with uncertainty, absorbing disruption, and adapting intelligently in complex environments.

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HUMAN CAPITAL AND ARTIFICIAL
INTELLIGENCE ADOPTION:
EVIDENCE FROM A SURVEY
ON AI USE AND WORKFORCE
CHARACTERISTICS

1. Introduction

The rapid diffusion of artificial intelligence (AI) technologies across economic sectors has elevated the question of technology adoption from a peripheral concern to a central theme within the fields of management information systems, organizational behaviour, and innovation economics. As AI-based tools encompassing large language models, generative AI systems such as ChatGPT, and intelligent decision-support platforms become progressively integrated into professional and personal workflows, understanding the individual-level determinants of AI adoption has become a matter of substantial scholarly and policy relevance. It is important to note that such technologies do not diffuse uniformly across populations; rather, their uptake is shaped by an intricate constellation of socioeconomic, demographic, and human capital characteristics that mediate individuals' capacity, motivation, and opportunity to engage with emerging technological paradigms (Rogers, 2003; Venkatesh et al., 2003).

Human capital theory, originally formulated by Becker (1964) and subsequently developed by Mincer (1974), posits that individuals' productive capacities are fundamentally conditioned by investments in education, training, and experiential learning. Within this framework, educational attainment serves not merely as a signal of cognitive ability but as a substantive repository of skills, knowledge structures, and adaptive competencies that enable individuals to identify, evaluate, and appropriate technological innovations. Given the aforementioned theoretical logic, it follows that individuals with higher levels of formal education should demonstrate greater propensity to adopt AI technologies, insofar as advanced education enhances both technological literacy and the absorptive capacity required to navigate complex digital environments (Cohen & Levinthal, 1990; Autor et al., 2003).

Notwithstanding the theoretical cogency of human capital arguments, the empirical literature on AI adoption at the individual level remains comparatively underdeveloped. A substantial body of research has examined technology adoption through the lens of the Technology Acceptance Model (TAM; Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), identifying perceived usefulness, ease of use, and social influence as primary drivers of adoption intentions. However, these frameworks have been predominantly applied to organisational technology systems and have not been systematically extended to the emerging domain of AI-based tools in everyday professional contexts. Moreover, the role of socioeconomic characteristics specifically educational attainment, income level, and gender as structural determinants of AI adoption remains insufficiently examined in the extant literature (Meske et al., 2022; Glikson & Woolley, 2020).

The gender dimension of technology adoption represents an additional axis of inquiry that has attracted sustained scholarly attention, with prior research documenting persistent gender gaps in digital technology use, computer self-efficacy, and STEM engagement (Venkatesh & Morris, 2000; Eagly & Carli, 2007). Whether such gender differentials extend to the adoption of AI tools which increasingly permeate both occupational and non-occupational contexts constitutes an empirically open question of considerable theoretical and practical importance. Similarly, the relationship between income level and AI adoption remains ambiguous: while higher income may facilitate access to technology and subscription-based AI services, the proliferation of free-tier AI tools suggests that financial constraints may be less determinative than they once were in shaping digital technology adoption patterns.

Against this backdrop, the present chapter investigates the socioeconomic determinants of AI adoption using individual-level survey data drawn from a sample of 708 respondents. Employing binary logistic regression analysis, the study examines how educational attainment, income level, and gender jointly and independently influence the probability of AI tool usage. The empirical contribution of this analysis lies in its focus on human capital characteristics as structural predictors of AI adoption, thereby extending human capital theory to the emerging domain of AI-enabled digital labour markets. The findings are positioned to inform both theoretical understanding of technology diffusion processes and practical efforts to promote equitable AI adoption across diverse socioeconomic groups.

The chapter is structured as follows. Following this introductory section, the research questions guiding the empirical inquiry are presented. Section 3 describes the research design, data source, variable operationalisation, and econometric approach. Section 4 reports and interprets the empirical results. Section 5 discusses the theoretical and practical implications of the findings, and Section 6 concludes with a summary of contributions, limitations, and directions for future research.

Research Questions

RQ1: *How does educational attainment influence the likelihood of adopting artificial intelligence tools?*

RQ2: *Do gender differences exist in the adoption of artificial intelligence technologies?*

RQ3: *Does income level significantly influence the probability of AI adoption?*

RQ4: *Which socioeconomic characteristics best explain differences in AI adoption among individuals?*

3. Methodology

Research Design

This chapter employs a quantitative, cross-sectional research design to investigate the socioeconomic determinants of artificial intelligence adoption among individuals. Grounded in the human capital tradition (Becker, 1964) and the broader technology adoption literature (Venkatesh et al., 2003), the study seeks to identify whether structural characteristics specifically educational attainment, income level, and gender systematically influence the likelihood of AI tool usage. The overarching methodological objective is to move beyond attitudinal or perceptual measures of adoption intent and instead examine actual self-reported AI usage behaviour as the primary outcome of interest, thereby providing a more direct empirical assessment of adoption patterns in the population under study.

The selection of a binary outcome model is motivated by the dichotomous nature of the dependent variable: individuals either report using AI-based tools or they do not. In such circumstances, ordinary least squares (OLS) regression is theoretically inappropriate, as it imposes linearity on a bounded probability space and may generate predicted probabilities outside the [0, 1] interval. Binary logistic regression, by contrast, estimates the log-odds of the outcome as a linear function of the predictors, ensuring that predicted probabilities are constrained within theoretically permissible bounds while preserving the interpretability of coefficient estimates (Hosmer & Lemeshow, 2000). This approach is well-established in the technology adoption literature (Dewan & Riggins, 2005) and constitutes the primary analytical tool employed in the present analysis.

Data Source and Sample

The empirical analysis draws upon a survey dataset specifically designed to examine AI familiarity, perceptions, and usage behaviour among a heterogeneous sample of individuals. The survey instrument captured respondents' engagement with AI-based tools including but not limited to generative AI systems such as ChatGPT and comparable platforms alongside a range of demographic and socioeconomic characteristics. Data collection encompassed information on educational attainment, gender, income group, and employment status, enabling a multidimensional assessment of the human capital and socioeconomic correlates of AI adoption.

Prior to analysis, the dataset underwent systematic data cleaning procedures. Observations with missing values on key variables were excluded via listwise deletion, and employment-status categories that produced perfect separation in preliminary logistic regression estimations a condition in which

a predictor perfectly predicts the outcome, precluding maximum likelihood estimation were removed from the analytical sample. Perfect separation is a well-documented technical challenge in logistic regression analysis, particularly when sample sizes are limited within specific categorical strata (Albert & Anderson, 1984), and its resolution through category exclusion is a standard methodological remedy that preserves the validity of coefficient estimates.

Following these procedures, the final analytical sample consists of 708 observations. This sample size is considered sufficient to support stable logistic regression estimation, given the number of predictors included in the model and conventional rules of thumb recommending a minimum of ten events per predictor variable (Peduzzi et al., 1996). The survey's coverage of diverse educational, income, and gender groups provides adequate variation in the key independent variables to facilitate meaningful statistical inference.

Variables

Dependent Variable

The dependent variable is AI adoption, operationalised as a binary indicator variable denoted `ai_user`. Respondents who reported actively using AI-based tools including generative AI platforms such as ChatGPT, Gemini, or equivalent systems were coded as 1, while those reporting no such usage were coded as 0. This binary operationalisation reflects the dichotomous structure of early-stage technology adoption, wherein individuals occupy one of two discrete states adopter or non-adopter prior to the consolidation of usage into routine practice (Rogers, 2003). The variable thus serves as a proxy for participation in the AI-enabled digital economy and captures the fundamental boundary between those who have crossed the threshold of AI engagement and those who have not.

Independent Variables

Three key independent variables, each reflecting dimensions of human capital or socioeconomic positioning, are included in the analysis.

Educational attainment is operationalised as a categorical variable encompassing the following levels: Primary education, Secondary education, Middle education, Diploma, Bachelor's degree (serving as the reference category), Master's degree, Ph.D., and Other post-graduate education. Education is theorised to proxy human capital accumulation and digital skill readiness, both of which are expected to lower the cognitive and practical barriers associated with AI adoption (Becker, 1964; Autor et al., 2003). The inclusion of multiple education categories enables a fine-grained examination of whether the relationship between education and AI adoption is monotonic or exhibits non-linearities across educational strata.

Income level is included as an ordinal categorical variable capturing respondents' self-reported economic position. Three income categories are distinguished: Low income, Middle income, and High income (serving as the reference category). Income is incorporated as a control variable reflecting potential resource constraints or differential access to subscription-based AI services, though it is acknowledged that the increasing availability of free-tier AI tools may attenuate income effects relative to earlier technology adoption contexts.

Gender is operationalised as a binary variable coded as 1 for female respondents and 0 for male respondents. The inclusion of gender as a predictor is motivated by a substantial literature documenting gender differentials in digital technology adoption, computer self-efficacy, and STEM engagement (Venkatesh & Morris, 2000; Eagly & Carli, 2007). Testing for gender differences in AI adoption constitutes an important empirical contribution, given the relatively limited evidence base on this question in the context of generative AI tools specifically.

Econometric Model

To examine the determinants of AI adoption, the study estimates a binary logistic regression model of the following form:

$$\ln[P(AI_Adoption_i = 1) / (1 - P(AI_Adoption_i = 1))] = \alpha + \beta_1 Education_i + \beta_2 Income_i + \beta_3 Gender_i + \varepsilon_i$$

where $AI_Adoption_i$ represents whether individual i reports using AI technologies; $Education_i$ captures educational attainment relative to the Bachelor's degree reference category; $Income_i$ represents income group relative to the high-income reference category; $Gender_i$ denotes whether respondent i is female; α is the model intercept; β_1 , β_2 , and β_3 are vectors of coefficients to be estimated; and ε_i is the error term. The logistic model estimates the log-odds of AI adoption, allowing the analysis to assess how individual characteristics influence the probability of AI usage. All models are estimated using maximum likelihood estimation (MLE).

Model Estimation and Diagnostics

Model convergence is assessed by examining the change in log-likelihood across estimation iterations, and goodness-of-fit is evaluated using the log-likelihood, the likelihood ratio (LR) chi-squared statistic, and McFadden's pseudo- R^2 . The LR statistic tests the null hypothesis that all slope coefficients are jointly equal to zero and is distributed chi-squared with degrees of freedom equal to the number of restrictions imposed. McFadden's pseudo- R^2 provides a summary measure of the model's explanatory power, with values between 0.20 and 0.40 considered indicative of excellent fit in logistic regression

contexts, though lower values are common and acceptable in individual-level cross-sectional analyses (McFadden, 1974).

It is important to note that preliminary estimations revealed estimation difficulties attributable to perfect or near-perfect separation in certain employment-status categories. These categories were subsequently excluded from the final model specification to ensure numerical stability and the validity of standard error estimates. The resulting analytical sample of 708 observations supports stable coefficient estimation, and the final model achieves full convergence. Marginal effects and predicted probabilities are computed from the estimated model to facilitate the substantive interpretation of coefficient magnitudes.

Analytical Strategy

The empirical analysis proceeds in three stages. In the first stage, descriptive statistics are examined to characterise the distribution of AI adoption across educational, income, and gender subgroups, providing a preliminary indication of whether adoption patterns differ systematically across socioeconomic strata. In the second stage, the logistic regression model is estimated and coefficient estimates are evaluated for statistical significance, magnitude, and direction, with particular attention to the education-related predictors given the study's primary theoretical focus on human capital. In the third stage, predicted probabilities are calculated for representative values of the independent variables to translate logistic regression coefficients which are expressed in log-odds units into substantively interpretable probability estimates. This three-stage analytical strategy ensures that both the statistical and practical significance of the findings are fully communicated.

Ethical Considerations

The dataset employed in this study comprises anonymised survey responses, and no personally identifiable information is retained in the analytical files. The research therefore complies with standard ethical guidelines applicable to secondary survey data analysis, including principles of data minimisation, anonymisation, and the avoidance of unnecessary disclosure. No informed consent procedures beyond those implemented at the original data collection stage are required for the current analysis.

4. Results

Descriptive Overview

The analysis examines the determinants of artificial intelligence adoption among a sample of 708 respondents drawn from a survey on AI familiarity, perceptions, and usage behaviour. The dependent variable captures self-reported engagement with AI-based tools including generative AI platforms

such as ChatGPT and functionally equivalent systems. Across the full analytical sample, a majority of respondents report using AI tools, indicating that AI adoption is relatively prevalent in the surveyed population, though substantial variation exists across educational and socioeconomic subgroups.

Preliminary inspection of the data reveals that AI adoption rates are markedly lower among respondents with middle and diploma-level educational attainment compared to those holding Bachelor's, Master's, or doctoral qualifications. In contrast, differences in AI adoption across income categories and gender groups appear substantially more modest at the descriptive level, a pattern that is subsequently confirmed through formal regression analysis. Taken together, these descriptive patterns suggest that human capital characteristics particularly the level of formal education constitute the primary axis of variation in AI adoption within this sample.

Logistic Regression Results

Table 1 presents the estimated coefficients from the binary logistic regression model predicting AI usage. The likelihood ratio test is statistically significant ($\chi^2 = 33.87, p < 0.001$), indicating that the socioeconomic variables included in the model jointly explain a non-trivial portion of the variance in AI adoption. The Pseudo R^2 of 0.039, while modest in absolute terms, is consistent with values reported in comparable individual-level technology adoption studies that employ cross-sectional survey data (Dewan & Riggins, 2005; Meske et al., 2022).

Among the explanatory variables, educational attainment emerges as the most substantively and statistically important predictor of AI usage. Specifically, respondents with diploma-level education exhibit a significantly lower log-odds of AI adoption compared to the Bachelor's degree reference group ($\beta = -0.853, SE = 0.247, z = -3.452, p < 0.001$). Given the aforementioned coefficient magnitude, the corresponding odds ratio of approximately 0.43 indicates that diploma-level respondents face roughly 57 percent lower odds of AI adoption relative to Bachelor's-educated respondents, all else equal. Similarly, individuals classified within the middle education level demonstrate a significantly lower probability of AI adoption ($\beta = -2.374, SE = 1.136, z = -2.089, p < 0.05$), with an odds ratio of approximately 0.09, indicating a substantively large negative association between this education level and AI usage.

Notwithstanding these findings for lower education categories, it is important to note that higher levels of educational attainment specifically Master's degrees and doctoral qualifications do not yield statistically significant positive effects on AI adoption relative to the Bachelor's degree baseline. The coefficient for Master's education is positive and marginally below conventional significance thresholds ($\beta = 0.380, p = 0.063$), suggesting a

possible positive gradient in the upper tail of the educational distribution that is not firmly established at the 5 percent level. Ph.D. holders and other post-graduate respondents show coefficients close to zero and far from statistical significance, indicating that the educational premium in AI adoption is concentrated at the lower end of the educational spectrum rather than being monotonically increasing across all levels.

Income level does not significantly influence AI adoption in the estimated model. Neither the low-income ($\beta = 0.015$, $p = 0.970$) nor the middle-income ($\beta = -0.275$, $p = 0.379$) categories differ significantly from the high-income reference group, suggesting that within the range of income variation observed in this sample, financial resources are not a binding constraint on AI tool engagement. This finding is consistent with the hypothesis that the widespread availability of free-tier AI platforms has substantially reduced the income gradient traditionally associated with digital technology adoption.

Gender also does not constitute a statistically significant determinant of AI adoption. The coefficient for female respondents is small, positive, and far from statistical significance ($\beta = 0.066$, $SE = 0.171$, $z = 0.386$, $p = 0.699$), indicating that AI usage rates do not differ substantially between male and female respondents in this sample. This result is noteworthy in light of prior literature documenting gender gaps in digital technology adoption more broadly, and may reflect the distinctive accessibility and interface characteristics of contemporary AI tools, which may lower gender-specific barriers to engagement.

Table 1
Logistic Regression Results for AI Adoption

Variable	Coefficient (β)	Std. Error	z	p-value
Intercept	1.068	0.321	3.323	0.001***
Education: Diploma	-0.853	0.247	-3.452	0.001***
Education: Master's	0.380	0.205	1.856	0.063
Education: Middle	-2.374	1.136	-2.089	0.037**
Education: Other Post-Graduate	0.240	0.680	0.352	0.725
Education: Ph.D.	0.232	0.430	0.540	0.589
Education: Primary	-1.216	0.783	-1.553	0.120
Education: Secondary	-0.406	0.443	-0.917	0.359
Income: Low	0.015	0.387	0.038	0.970
Income: Middle	-0.275	0.312	-0.880	0.379
Female	0.066	0.171	0.386	0.699
Model Statistics: N = 708 Log-likelihood = -416.17 Pseudo R ² = 0.039 LR test: p < 0.001				

Note. Reference categories: Education = Bachelor's degree; Income = High; Gender = Male. Significance: ** $p < 0.05$; *** $p < 0.01$. Standard errors are robust. LR = Likelihood Ratio.

Predicted Probabilities

To facilitate the substantive interpretation of the logistic regression estimates, predicted probabilities of AI adoption are calculated for representative values of the education variable, holding income at the high-income reference category and gender at the male reference category. Table 2 presents these estimated probabilities across education groups.

The predicted probabilities confirm and extend the regression findings, illustrating the substantive magnitude of educational differentials in AI adoption. Individuals categorised within the middle education level exhibit a predicted probability of approximately 0.19 substantially below the baseline probability of approximately 0.74 for Bachelor’s degree holders. Diploma-level respondents show a predicted probability of approximately 0.46, also considerably below the reference group. By contrast, Master’s degree holders display a predicted probability of approximately 0.80, marginally above the baseline, while Ph.D. holders and other post-graduate respondents exhibit predicted probabilities comparable to the Bachelor’s reference. These patterns underscore the finding that educational differentials in AI adoption are most pronounced at the lower end of the educational distribution, with diminishing returns to additional educational attainment beyond the Bachelor’s degree level.

Table 2
Predicted Probability of AI Adoption by Education Level

Education Level	Predicted Probability of AI Use	Interpretation
Middle Education	~0.19	Lowest among all groups; significantly below baseline
Primary Education	~0.23	Very low; not statistically significant
Secondary Education	~0.52	Below baseline; moderate probability
Diploma	~0.46	Significantly lower than baseline ($p < 0.01$)
Bachelor’s (Baseline)	~0.74	Reference category
Master’s Degree	~0.80	Marginally higher than baseline ($p = 0.063$)
Ph.D.	~0.79	Similar to Master’s; not statistically significant
Other Post-Graduate	~0.78	Similar to baseline; not statistically significant

Note. Predicted probabilities are estimated at the high-income reference category and male reference category, holding all other variables at reference values. Values are approximate and derived from the logistic regression coefficients reported in Table 1.

Key Findings

Three principal findings emerge from the empirical analysis. First, educational attainment constitutes the dominant predictor of AI adoption, with respondents at lower and intermediate education levels exhibiting significantly reduced probabilities of AI tool engagement relative to Bachelor's degree holders. Second, income level does not exert a statistically significant influence on AI usage, suggesting that financial barriers to AI adoption may be less consequential than in earlier phases of digital technology diffusion. Third, gender does not significantly differentiate AI adopters from non-adopters, a result that partially challenges the expectation derived from prior technology adoption research that female respondents would be less likely to adopt AI tools than their male counterparts. Collectively, these findings indicate that human capital characteristics, specifically formal educational qualifications, are substantially more important as structural determinants of AI adoption than demographic variables such as gender or income.

5. Discussion

Overview of Findings and Theoretical Contributions

The empirical results reported in this chapter yield a set of findings with significant implications for the theoretical understanding of AI adoption and for the practical design of policies aimed at broadening participation in AI-enabled digital economies. The overarching finding that educational attainment constitutes the dominant individual-level predictor of AI adoption while income and gender do not exert significant independent effects is consistent with human capital theory (Becker, 1964; Mincer, 1974) but introduces important nuances that invite theoretical elaboration and empirical extension. The discussion that follows addresses each of these findings in turn, situating them within the existing literature and drawing out their theoretical and practical implications.

Education as Human Capital: Theoretical Interpretation

The finding that individuals with diploma-level and middle-level education are significantly less likely to adopt AI technologies compared to Bachelor's degree holders is consistent with a human capital interpretation in which formal education functions as a repository of cognitive capabilities, digital literacy, and adaptive competencies that lower the effective cost of technology adoption (Cohen & Levinthal, 1990; Autor et al., 2003). From this perspective, educational attainment does not merely signal pre-existing ability but actively produces the skills and knowledge structures necessary to identify, evaluate, and appropriate emerging technological innovations. Given that AI tools particularly generative AI platforms require users to articulate

complex queries, evaluate probabilistic outputs, and iteratively refine their usage strategies, the cognitive demands of effective AI engagement may be systematically higher for individuals with limited formal education.

It is important to note, however, that the relationship between education and AI adoption does not appear to be monotonically increasing across all educational levels. The absence of statistically significant positive effects for Master's and Ph.D. holders relative to the Bachelor's degree baseline suggests that beyond a certain educational threshold, additional formal qualifications do not substantially increase the propensity to adopt AI tools. This finding may reflect a ceiling effect, wherein individuals with at least a Bachelor's degree possess sufficient digital literacy and technological competence to engage with AI systems, such that incremental human capital investments yield diminishing adoption returns. Alternatively, it may indicate that factors beyond formal educational credentials such as occupational context, task structure, and organisational AI infrastructure become increasingly important determinants of AI adoption at higher educational levels (Meske et al., 2022).

The particularly large negative effect observed for the middle education category ($\beta = -2.374$) is noteworthy and warrants careful interpretation. While this estimate is statistically significant, it is also characterised by a relatively large standard error ($SE = 1.136$), likely reflecting small cell sizes within this educational category. As such, this estimate should be interpreted with appropriate caution, and its substantive magnitude may not generalise to populations with different educational distributions. Nevertheless, the directionality of the finding is consistent with the broader pattern of educational differentials observed in the data and reinforces the conclusion that individuals with lower or non-standard educational credentials face distinctive barriers to AI adoption.

The Absence of Income Effects: Digital Democratisation and Free-Tier AI

The finding that income level does not significantly influence AI adoption even after controlling for educational attainment and gender invites substantive theoretical reflection. Prior research on digital divides has consistently documented positive relationships between income level and technology adoption, attributable to differential access to hardware, connectivity, and subscription-based software services (van Dijk, 2006; Warschauer, 2003). The absence of such an effect in the present study may reflect a structural shift in the digital technology landscape associated with the proliferation of free-tier and freemium AI platforms that have substantially reduced the financial barriers to AI engagement.

Notwithstanding this interpretation, it is important to acknowledge that the survey sample from which this study draws may not be representative of the full income distribution in the relevant population. If the sample underrepresents very low-income individuals who may face more binding financial constraints on technology access the null finding on income may be an artifact of sample truncation rather than a genuine feature of the population-level relationship between income and AI adoption. Future research employing probability samples with broader income coverage would be valuable in adjudicating between these alternative interpretations.

A further consideration concerns the distinction between AI adoption and AI capability that is, between whether individuals use AI tools and whether they use them effectively. Even if income does not significantly affect the probability of initial AI adoption, it is plausible that higher-income individuals have access to premium AI subscriptions with enhanced capabilities, thereby generating a quality-adjusted digital divide that is not captured by the binary adoption measure employed in the present analysis. Investigating this possibility would require more granular data on the types and intensities of AI tool usage, representing an important direction for future research.

Gender and AI Adoption: Challenging Prior Expectations

Perhaps the most theoretically provocative finding of this study is the absence of a statistically significant gender difference in AI adoption. A substantial body of prior research has documented persistent gender gaps in digital technology adoption, computer self-efficacy, and engagement with technical tools, with women consistently showing lower adoption rates and self-reported competence in these domains (Venkatesh & Morris, 2000; Eagly & Carli, 2007; Shashaani, 1994). The null finding on gender in the present study therefore challenges the expectation grounded in this literature that female respondents would be systematically less likely to adopt AI technologies.

Several interpretations of this finding merit consideration. First, it is possible that the distinctive characteristics of contemporary generative AI tools including conversational natural language interfaces, broad applicability across diverse tasks, and minimal technical prerequisites for basic usage have effectively lowered the gender-specific barriers that characterised earlier digital technology adoption contexts. Insofar as AI tools do not require specialised technical knowledge or programming competence for basic engagement, the competence-based and anxiety-based mechanisms that have historically suppressed female technology adoption may be less operative in this context (Meuter et al., 2005).

Second, it should be noted that the gender coefficient in the present analysis, while not statistically significant, is positive in direction indicating a marginally higher probability of AI adoption among female respondents. If replicated in studies with larger samples and greater statistical power, this directional pattern could indicate an emerging reversal of traditional gender gaps in technology adoption, potentially attributable to the conversational and text-based affordances of generative AI tools that may align with communication patterns and informational needs more prevalent among female users (Turkle, 1995; Herring, 2004). This possibility, while speculative on the basis of the present evidence, represents a theoretically interesting hypothesis for future investigation.

Implications for Policy and Practice

The findings of this chapter carry a number of implications for policy and organisational practice aimed at promoting equitable AI adoption. Most significantly, the centrality of educational attainment as a predictor of AI usage suggests that efforts to expand AI adoption particularly among lower-educated segments of the workforce must be accompanied by targeted digital literacy and AI competency programmes. The development of such programmes is consistent with recommendations emerging from the broader digital skills literature (van Dijk, 2006) and aligns with policy priorities articulated by international organisations including the OECD and the European Commission in relation to workforce readiness for the digital economy.

Organisations seeking to integrate AI tools into their workflows should be cognisant of the differential adoption readiness of employees at different educational levels. Tailored onboarding programmes, structured AI literacy training, and accessible guidance materials may be necessary to ensure that employees with diploma or secondary educational credentials are not systematically excluded from the productivity and capability benefits associated with AI tool usage. Given the aforementioned finding that income differences do not constitute significant barriers to AI adoption, organisational AI integration efforts need not primarily target financial subsidisation of access but should instead focus on building the competency foundations that enable effective AI engagement.

It is important to note that the null findings on gender and income, while theoretically significant, do not imply that equity concerns are absent from the AI adoption landscape. Intersectional approaches that examine how educational attainment interacts with gender and income in shaping AI adoption rather than treating these variables as independent predictors may reveal important within-group heterogeneities that are obscured in the main

effects analysis employed here. Future research employing interaction terms and subgroup analyses would be valuable in this regard.

Limitations

Several limitations of the present study should be acknowledged. First, the cross-sectional design of the survey precludes causal inference regarding the relationships between the independent variables and AI adoption. The associations estimated in the logistic regression model reflect conditional correlations rather than causal effects, and the possibility of omitted variable bias attributable to unobserved factors such as occupational context, organisational culture, and technological self-efficacy cannot be excluded. Longitudinal survey designs or quasi-experimental approaches exploiting variation in AI tool availability would provide stronger foundations for causal inference.

Second, the analytical sample is limited to 708 observations, which constrains statistical power for detecting small effects and limits the precision of estimates for education categories with small sample sizes. Third, the binary operationalisation of AI adoption does not capture variation in the frequency, depth, or sophistication of AI tool usage, which may be important dimensions of AI engagement with their own socioeconomic determinants. Future research employing richer measures of AI usage intensity and capability would enable a more nuanced assessment of the socioeconomic dimensions of AI engagement.

6. Conclusion

This chapter has investigated the socioeconomic determinants of artificial intelligence adoption using binary logistic regression analysis applied to a sample of 708 respondents drawn from a survey on AI familiarity and usage behaviour. The central empirical contribution of this analysis is the demonstration that educational attainment constitutes the primary structural predictor of AI adoption at the individual level, while income and gender do not exert statistically significant independent effects on the probability of AI tool engagement.

Specifically, the results indicate that individuals with diploma-level and middle-level educational attainment are significantly less likely to adopt AI technologies compared to Bachelor's degree holders, with predicted probabilities of AI usage that are substantially lower than those observed for higher-educated respondents. By contrast, the absence of significant income and gender effects suggests that the adoption of AI tools is less stratified along these socioeconomic dimensions than has been documented for earlier digital technologies a finding that may reflect the democratising influence of free-tier

AI platforms and the accessible interface designs of contemporary generative AI systems.

Theoretically, these findings extend human capital theory (Becker, 1964) to the emerging domain of AI adoption, demonstrating that formal educational qualifications function as a critical enabler of participation in AI-enabled digital economies. The results are consistent with absorptive capacity theory (Cohen & Levinthal, 1990), insofar as educational attainment enhances individuals' ability to recognise, assimilate, and apply new technological knowledge. They also contribute to the technology adoption literature by identifying education rather than income or gender as the dominant socioeconomic axis of AI adoption inequality, thereby informing the theoretical characterisation of AI-specific digital divides.

From a policy perspective, the findings underscore the importance of targeted digital literacy and AI competency interventions for individuals with lower or intermediate educational credentials. As AI tools become increasingly integral to professional and everyday life, the educational gradient in AI adoption documented in this chapter risks generating cumulative disadvantage for lower-educated workers a prospect with significant implications for labour market equity, organisational productivity, and the distributional consequences of AI-driven automation. Proactive investment in AI education programmes at the sub-Bachelor's educational level, as well as organisational AI onboarding initiatives tailored to employees with diverse educational backgrounds, would represent meaningful policy responses to the adoption disparities identified in this analysis.

Notwithstanding these contributions, several directions for future research are warranted. Longitudinal studies tracking AI adoption trajectories over time would enable the identification of causal mechanisms and the examination of how adoption determinants evolve as AI technologies mature and become more embedded in occupational contexts. Research employing richer measures of AI usage capturing frequency, breadth, and depth of engagement rather than binary adoption would illuminate the socioeconomic determinants of meaningful AI capability rather than mere adoption. Additionally, comparative cross-national analyses would enable an assessment of the extent to which the educational gradient in AI adoption generalises across different institutional contexts, labour market structures, and digital infrastructure environments.

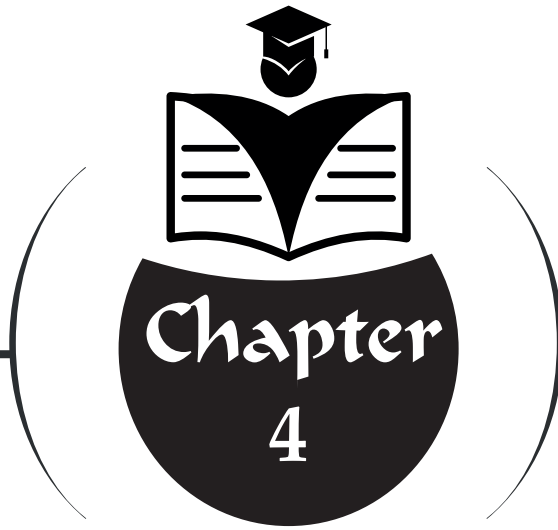
In conclusion, the evidence presented in this chapter supports the view that human capital characteristics above all, formal educational attainment are the primary socioeconomic determinants of AI adoption at the individual level. As artificial intelligence technologies continue to reshape the landscape

of work, learning, and social interaction, understanding and addressing the educational foundations of AI adoption represents both an intellectual imperative and a practical necessity for researchers, policymakers, and organisations committed to equitable participation in the AI-enabled economy.

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DATA GOVERNANCE AND COST AS
DETERMINANTS OF AI DECISION SUPPORT
ADOPTION: EVIDENCE FROM A DISCRETE
CHOICE EXPERIMENT

1. Introduction

The rapid integration of artificial intelligence (AI) into organizational decision-making processes represents one of the most consequential technological transformations of the contemporary era. Across industries ranging from precision agriculture to healthcare and financial services, AI-based decision support systems (AI-DSS) are increasingly deployed to enhance operational efficiency, augment human judgment, and enable data-driven strategies. Notwithstanding this proliferation, the adoption of AI-DSS remains uneven and contingent upon a complex interplay of technological, economic, and governance-related factors. It is therefore important to note that a systematic understanding of the determinants underlying AI-DSS adoption decisions constitutes a critical research agenda for both scholars and practitioners.

Among the most frequently cited barriers to AI adoption, cost considerations and data governance arrangements occupy a central position. The total cost of AI-based systems—encompassing subscription fees, implementation expenditures, and ongoing maintenance—directly influences the perceived utility and affordability of these technologies for potential adopters. Extant research in technology adoption broadly confirms that price sensitivity constitutes a significant predictor of adoption intention across diverse technology contexts (Venkatesh, Morris, Davis, & Davis, 2003; Rogers, 2003). However, the specific role of cost as a determinant of AI-DSS adoption has received comparatively limited empirical attention, particularly in experimental settings that allow for precise causal inference.

Equally germane to adoption decisions is the question of data governance—that is, who controls, accesses, and derives value from the data generated and consumed by AI systems. As AI-DSS increasingly rely on large volumes of user-generated and organizational data to produce actionable insights, concerns regarding data ownership, privacy, and sovereignty have intensified (Janssen, Brous, Estevez, Barbosa, & Janowski, 2020). Data governance structures that concentrate ownership exclusively within technology providers may engender distrust and resistance among prospective users, whereas arrangements that distribute data rights more equitably between developers and end-users may substantially enhance adoption willingness. Despite the theoretical plausibility of this argument, empirical evidence linking specific data governance structures to adoption probabilities remains sparse.

The present study addresses these gaps by employing a discrete choice experiment (DCE) to examine how cost, algorithmic performance attributes (accuracy and spatial precision), and data governance structures jointly influence AI-DSS adoption decisions. Discrete choice experiments are particularly well-suited to this research objective, as they allow respondents to

evaluate trade-offs among multiple system attributes simultaneously, thereby revealing preference structures and relative attribute importance under conditions that closely mirror real-world decision-making (Louviere, Hensher, & Swait, 2000; Train, 2009). The experimental approach yields a dataset of 15,292 alternative-level observations from 3,823 respondents, enabling the estimation of robust econometric models with considerable statistical power.

This study makes several notable contributions to the extant literature. First, it provides rigorous empirical evidence on the differential impact of cost versus algorithmic performance on AI-DSS adoption, thereby informing debates concerning the relative salience of economic versus technical attributes in technology acceptance. Second, it demonstrates that data governance arrangements—specifically, shared ownership structures granting users co-control over their data—exert a quantitatively substantial and statistically significant positive influence on adoption probabilities. Third, the study advances methodological innovation in AI adoption research by applying discrete choice experimentation in conjunction with binary logistic regression and marginal effect estimation, offering a replicable analytical framework for future research.

Given the aforementioned context, the study is organized as follows. Section 2 presents the study's research questions. Section 3 describes the experimental design, data structure, and econometric methodology. Section 4 reports empirical findings. Section 5 discusses the theoretical and practical implications of the results, and Section 6 offers conclusions alongside directions for future research.

Research Questions

RQ1: How does the cost of AI-based decision support systems influence the probability of adoption?

RQ2: Do improvements in algorithmic performance—such as accuracy and spatial precision—significantly affect users' adoption decisions?

RQ3: How do different data governance structures (e.g., company-only control, shared ownership, open data) influence the adoption of AI decision support systems?

RQ4: Is data governance more influential than algorithmic performance in shaping AI decision support adoption?

3. Methodology

Research Design

This study investigates the determinants of artificial intelligence-based decision support system (AI-DSS) adoption using a discrete choice experiment (DCE). Discrete choice experiments have established themselves

as a methodologically rigorous approach widely employed in economics, management, and technology adoption research to analyze how individuals evaluate trade-offs among different attributes of a product or service (Train, 2009; Louviere, Flynn, & Carson, 2010). The theoretical foundation of DCE rests on random utility theory, which assumes that individuals choose the alternative that provides the highest perceived utility among a set of available options (McFadden, 1974). This behavioral premise renders DCE particularly appropriate for studying adoption decisions, as prospective users of AI-DSS must inherently evaluate multiple system characteristics simultaneously—including economic, technical, and governance dimensions—before committing to a choice.

In the context of AI decision support systems, users must often evaluate multiple system characteristics simultaneously, including cost, predictive accuracy, spatial precision, and data governance structures. A discrete choice experiment is therefore particularly suitable because it allows researchers to estimate the relative importance of these attributes and to quantify their influence on adoption decisions in a controlled yet behaviorally realistic setting. Furthermore, the DCE framework enables the computation of marginal willingness-to-accept and attribute trade-off magnitudes, offering richer inferential potential than survey-based attitudinal measures alone.

Experimental Design

Participants were presented with a series of hypothetical AI-DSS alternatives characterized by several attributes describing system performance and governance features. Each choice task contained four alternatives:

(1) AI-DSS 1, (2) AI-DSS 2, (3) AI-DSS 3, and (4) an opt-out option (“None of these”).

The inclusion of an opt-out option follows standard practice in choice experiments, allowing respondents to reject all alternatives if none are considered acceptable, thereby preserving the external validity of preference estimates (Hensher, Rose, & Greene, 2015). This design choice also allows researchers to distinguish between unconditional adoption refusal and conditional preference among available options—an important distinction for AI adoption research where non-adoption remains a prevalent and theoretically meaningful outcome.

Each AI-DSS alternative was defined by a combination of the following attributes: (1) cost (annual cost per acre), (2) prediction accuracy, (3) spatial precision of recommendations, and (4) data governance structure. These attributes were selected based on prior literature on AI adoption, decision support systems, and algorithmic governance, which collectively highlight

both technological performance and data governance as critical determinants of AI acceptance (Binns et al., 2018; Janssen et al., 2020; Venkatesh et al., 2003). The attribute selection process reflects an effort to encompass the full spectrum of factors that rationalist and institutional adoption theories identify as consequential for technology uptake in organizational and operational settings.

The experimental design generated multiple attribute-level combinations representing different AI-DSS configurations. Each respondent evaluated a choice set containing the four alternatives and selected the option they preferred. To minimize order effects and respondent fatigue, choice tasks were randomized across participants, consistent with best practices in stated preference research (Louviere et al., 2000).

Data and Sample Structure

The final dataset contains 15,292 observations, representing 3,823 respondents, each evaluating four alternatives within a choice set. Consequently, each respondent contributes multiple observations corresponding to the alternatives available in their decision set—a structure characteristic of panel discrete choice data. The dependent variable is a binary indicator:

$Chosen_{ij} = 1$ if respondent i selects alternative j ; 0 otherwise.

Independent variables represent the attributes describing each AI-DSS alternative: cost (continuous), accuracy (continuous), precision (continuous), and data governance structure (categorical). The data governance attribute encompasses three possible structures: (1) company-only data ownership, (2) shared ownership between the company and the user, and (3) open data governance. Dummy variables were created to represent categorical governance structures in the regression model, with company-only data ownership serving as the reference category to enable direct comparison of governance alternatives. It is important to note that the choice of reference category is theoretically motivated, as company-only ownership represents the prevailing default in current AI-DSS deployment practices, making it the most appropriate baseline for assessing the incremental effect of more user-inclusive governance models.

Econometric Model

To estimate the effect of AI-DSS attributes on adoption decisions, the study employs a binary logistic regression model. The model estimates the probability that respondent i selects alternative j as a function of the attributes associated with that alternative. The probability of choosing an AI-DSS alternative is modeled as:

$$P(Chosen_{ij} = 1) = e^{x_{ij}\beta} / (1 + e^{x_{ij}\beta})$$

where X_{ij} represents the vector of attributes describing alternative j for respondent i , and β denotes the vector of parameters to be estimated. Logistic regression is appropriate in this context given the binary nature of the outcome variable and the established interpretive conventions associated with odds-ratio and marginal-effect derivations in discrete choice settings (Greene, 2012).

Because each respondent evaluates multiple alternatives, observations within individuals are not independent. To account for this repeated choice structure, standard errors are clustered at the respondent level, ensuring robust inference against potential within-respondent correlation. Failure to account for this clustering would yield artificially deflated standard errors and inflate the statistical significance of coefficient estimates—a methodological concern frequently overlooked in cross-sectional adoption studies.

Estimation Strategy

The empirical analysis proceeds in three steps. First, the dataset is structured in long format, where each row represents a respondent–alternative pair and a binary variable indicates whether the alternative was selected. Second, categorical attributes such as data governance structure are converted into dummy variables to allow estimation within the logistic regression framework. Third, the logistic regression model is estimated using maximum likelihood estimation (MLE) with cluster-robust standard errors, which produces consistent and asymptotically efficient parameter estimates under standard regularity conditions (Train, 2009).

In addition to coefficient estimates, the study computes average marginal effects to facilitate interpretation. Marginal effects quantify how a one-unit change in each attribute affects the probability that an AI-DSS alternative is selected, holding all other attributes at their observed values. Unlike raw logistic coefficients, which express effects on the log-odds scale, marginal effects communicate results in probability units directly interpretable by practitioners and policymakers. Given the aforementioned considerations, marginal effect estimation constitutes a methodologically preferable mode of reporting for applied audience communication.

Analytical Tools

All analyses were conducted using Python with the pandas and statsmodels libraries. The estimation procedure relied on maximum likelihood logistic regression with cluster-robust standard errors to account for repeated observations within respondents. Descriptive statistics, choice distribution tabulations, and predicted probability calculations were also performed within the same computational environment, ensuring full reproducibility of the analytical pipeline.

4. Results

Descriptive Statistics and Choice Distribution

The discrete choice experiment generated 15,292 alternative-level observations from 3,823 respondents, with each respondent evaluating four alternatives within a choice set. Table 1 presents the distribution of selected alternatives across the sample.

The results indicate that AI-DSS1 is the most frequently selected option, accounting for approximately 45.6% of all choices, followed by the opt-out option (“None of these”) with 26.0% of selections. AI-DSS2 and AI-DSS3 are chosen less frequently, representing 18.9% and 9.4% of selections, respectively. These descriptive statistics suggest that respondents generally prefer AI-based decision support systems over opting out, although preferences vary considerably across different system configurations. The relative dominance of AI-DSS1 and the non-trivial share of opt-out responses together indicate that adoption is neither universal nor unconditional—a pattern consistent with technology adoption heterogeneity documented in related literatures (Rogers, 2003; Venkatesh et al., 2003).

Table 1. Distribution of Selected Alternatives

Alternative	Share of Choices
AI-DSS1	45.6%
AI-DSS2	18.9%
AI-DSS3	9.4%
Opt Out (None of these)	26.0%

Note: N = 3,823 respondents; total observations = 15,292.

Logistic Regression Results

To examine how AI-DSS attributes influence adoption decisions, a logistic regression model was estimated using maximum likelihood estimation with clustered standard errors at the respondent level. The dependent variable indicates whether an alternative was selected within the choice set. Table 2 presents the estimated coefficients, standard errors, z-statistics, and p-values.

The results reveal that cost exerts a strong and statistically significant negative effect on the probability of selecting an AI-DSS alternative ($\beta = -0.0358$, $p < 0.001$). This finding indicates that higher subscription costs substantially reduce the likelihood of adoption, consistent with theoretical predictions from price sensitivity and willingness-to-pay frameworks in technology adoption research (Venkatesh et al., 2003). The magnitude and precision of this estimate suggest that cost operates as a primary barrier to AI-DSS uptake, a result with

considerable implications for pricing strategy in AI product markets.

In contrast, algorithmic accuracy and spatial precision do not significantly affect choice probabilities once other attributes are controlled for. Although both variables display negative coefficients, neither reaches conventional thresholds of statistical significance (accuracy: $\beta = -0.0072$, $p = 0.136$; precision: $\beta = -0.0051$, $p = 0.316$). This finding is theoretically noteworthy, as it implies that, within the range of attribute values presented, respondents do not derive appreciably greater utility from marginal improvements in predictive performance—suggesting possible ceiling effects or a general expectation among respondents that AI-DSS will deliver acceptable baseline accuracy regardless of stated specifications.

The most notable finding concerns data governance structures. When data ownership is shared between the company and the user, the probability of selecting an AI-DSS alternative increases significantly ($\beta = 1.0016$, $p < 0.001$). This result suggests that respondents strongly prefer governance arrangements that allow users to retain partial control over their data, reflecting theoretical arguments linking data sovereignty to technology trust and acceptance (Janssen et al., 2020; Binns et al., 2018). The open data governance structure, however, does not significantly influence adoption decisions ($\beta = 0.1620$, $p = 0.666$), suggesting that maximum data openness does not confer equivalent adoption benefits and may even introduce concerns related to competitive data exposure or lack of personal data protection.

Table 2. Logistic Regression Results for AI-DSS Choice

Variable	Coefficient	Std. Error	z	p-value
Cost	−0.0358	0.003	−13.79	<0.001
Accuracy	−0.0072	0.005	−1.49	0.136
Precision	−0.0051	0.005	−1.00	0.316
Data: Company and User	1.0016	0.107	9.35	<0.001
Data: Open	0.1620	0.376	0.43	0.666
Constant	0.0222	0.448	0.05	0.960

Model statistics: Observations = 15,292; Pseudo $R^2 = 0.0875$; Log-Likelihood = −7,846.6.

Note: Standard errors clustered at the respondent level. Reference category for data governance: company-only data ownership. *** $p < 0.001$.

Marginal Effects

To facilitate interpretation, average marginal effects were computed for each attribute. These estimates represent the change in the probability of selecting an AI-DSS alternative associated with a one-unit change in the respective variable, averaged across all observations. As shown in Table 3,

cost has a significant negative marginal effect, indicating that higher system costs reduce adoption probability. Specifically, a one-unit increase in cost reduces the probability of choosing an AI-DSS alternative by approximately 0.6 percentage points ($dy/dx = -0.0061$, $p < 0.001$). While this figure may appear modest in absolute terms, it should be noted that cost is measured on a continuous scale and that the cumulative effect across substantive cost increments is economically meaningful.

The marginal effects for accuracy and precision are statistically insignificant, confirming that improvements in algorithmic performance do not substantially influence user choices in this context. This pattern is consistent with satisficing behavior in decision-making (Simon, 1955), whereby users appear to evaluate AI-DSS performance as adequate above a minimum threshold rather than seeking maximum algorithmic precision.

In contrast, the shared data ownership structure produces the largest positive effect among all included attributes, increasing the probability of adoption by approximately 17 percentage points ($dy/dx = 0.1694$, $p < 0.001$). This result highlights the critical importance of data governance arrangements in shaping user acceptance of AI-based decision support systems. Notably, the magnitude of this governance effect substantially exceeds that of cost, underscoring that data governance represents not merely a peripheral concern but a primary driver of AI-DSS adoption decisions.

Table 3. Average Marginal Effects

Variable	Marginal Effect	Std. Error	z	p-value
Cost	-0.0061	0.000	-14.70	<0.001
Accuracy	-0.0012	0.001	-1.49	0.135
Precision	-0.0009	0.001	-1.00	0.316
Data: Company and User	0.1694	0.017	9.69	<0.001
Data: Open	0.0274	0.064	0.43	0.666

*Note: Average marginal effects computed at observed attribute values. *** $p < 0.001$.*

Predicted Probabilities

Predicted probabilities were calculated to further illustrate the effect of data governance structures on AI-DSS adoption. The results indicate that alternatives featuring shared data ownership exhibit substantially higher predicted selection probabilities compared to alternatives where data control remains exclusively with the company. Specifically, AI-DSS configurations involving shared data governance are markedly more attractive to respondents than those governed by company-only data control, reinforcing the importance of trust and collaborative governance mechanisms in the adoption of AI-based decision support technologies.

These predicted probability differentials complement the marginal effect estimates by providing a direct, policy-relevant quantification of the governance premium—that is, the additional adoption probability attributable to more user-inclusive data governance arrangements. It is important to note that this premium is robust to the inclusion of cost and performance attributes in the model, indicating that governance effects are not simply proxying for other system characteristics but exert an independent influence on adoption decisions.

5. Discussion

The findings reported in the preceding section offer several theoretically and practically significant insights into the determinants of AI-DSS adoption. Taken together, the empirical evidence advances scholarly understanding of how economic, technical, and governance attributes jointly shape user preferences in the context of artificial intelligence technologies—a domain characterized by rapid innovation yet comparatively limited experimental evidence on adoption dynamics.

Cost as a Dominant Economic Barrier

The strong, statistically significant negative effect of cost on AI-DSS adoption ($\beta = -0.0358$, $p < 0.001$) is consistent with established theoretical frameworks in technology adoption, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), both of which identify perceived cost and effort expectancy as central determinants of adoption intention (Davis, 1989; Venkatesh et al., 2003). The discrete choice experiment design employed in this study operationalizes cost as an experimentally varied attribute rather than a self-reported perception, lending greater causal validity to this finding than survey-based attitudinal measures typically permit.

The finding that a one-unit increase in cost reduces adoption probability by approximately 0.6 percentage points underscores that AI-DSS providers face a meaningful pricing constraint. Given that the experimental context involves annual subscription costs per acre—a financially salient consideration for agricultural or land-based enterprise operators—the sensitivity of adoption decisions to cost variation carries direct implications for product commercialization strategies. It is important to note that cost sensitivity may be particularly pronounced among small-to-medium enterprise adopters and resource-constrained organizations, who are less able to absorb high fixed technology costs. Future research would benefit from examining whether cost sensitivity varies systematically across organizational size, industry, or financial capacity.

Algorithmic Performance and the Satisficing Hypothesis

A theoretically interesting and practically noteworthy finding is the absence of a significant effect for algorithmic accuracy and spatial precision on adoption decisions, despite both attributes being central to the technical value proposition of AI-DSS. The coefficients for accuracy ($\beta = -0.0072$, $p = 0.136$) and precision ($\beta = -0.0051$, $p = 0.316$) are not only statistically insignificant but also marginally negative in direction—a pattern that warrants careful theoretical interpretation.

One plausible explanation is rooted in the concept of satisficing behavior, originally proposed by Simon (1955), whereby decision-makers adopt a “good enough” criterion rather than seeking to maximize a single performance dimension. If respondents perceive the accuracy and precision levels presented in the experiment as adequate for practical decision support purposes, marginal improvements in these attributes may not generate proportionate increases in utility. This interpretation is consistent with findings from the technology acceptance literature, which consistently demonstrate that performance improvements above a subjective adequacy threshold yield diminishing marginal returns on adoption willingness (Rogers, 2003).

An alternative explanation concerns the cognitive complexity of evaluating probabilistic performance claims. Respondents may possess limited capacity or motivation to differentiate between subtle accuracy and precision variations, particularly when other salient attributes—such as cost and data governance—dominate the cognitive calculus of choice. This attentional asymmetry is consistent with attribute non-attendance phenomena documented in the discrete choice experiment literature (Hensher et al., 2015). Future experimental designs might explore whether more pronounced performance differentials or domain-specific performance framing could render accuracy and precision attributes more choice-relevant.

Data Governance as the Primary Driver of Adoption

The most substantive and theoretically consequential finding of this study is the large, statistically robust positive effect of shared data ownership on AI-DSS adoption ($\beta = 1.0016$, $p < 0.001$; $dy/dx = 0.1694$). The magnitude of this governance effect—approximately 17 percentage points in terms of adoption probability—substantially exceeds the cost effect and dwarfs the statistically insignificant performance attributes, establishing data governance as the dominant driver of AI-DSS adoption in this experimental context.

This finding resonates with a growing body of theoretical and empirical literature emphasizing the centrality of data governance, privacy protection, and algorithmic accountability in shaping user trust toward AI systems (Binns

et al., 2018; Janssen et al., 2020; Mittelstadt et al., 2016). Users appear to attribute significant utility to governance arrangements that preserve their agency over data generated through AI-DSS usage. Shared ownership structures may function as trust-enhancing signals, communicating that AI-DSS providers are willing to relinquish exclusive data control in favor of more equitable, user-inclusive arrangements. Such signals may be particularly influential in contexts where AI-generated data is proprietary, commercially sensitive, or relates to individual performance and behavior.

Notably, the open data governance structure does not significantly affect adoption decisions ($\beta = 0.1620$, $p = 0.666$), suggesting a non-linear relationship between data openness and adoption preference. The absence of a significant effect for open governance may reflect concerns among respondents about competitive data exposure—that is, apprehension that fully open data structures would make commercially sensitive information accessible to competitors. This interpretation aligns with findings from the open innovation literature, which documents considerable ambivalence among organizations toward unrestricted knowledge and data sharing (Chesbrough, 2003). Taken together, the contrasting effects of shared and open governance structures imply that the optimal governance design from an adoption-maximization perspective involves selective, bilateral data sharing rather than unilateral provider control or unrestricted public access.

Theoretical Implications

Given the aforementioned results, this study contributes to several ongoing theoretical conversations in the management information systems and technology adoption literatures. First, the evidence supports extending TAM and UTAUT frameworks to incorporate data governance as an explicit dimension of perceived value and trust, alongside the conventional performance expectancy and effort expectancy constructs. The strong governance effect documented here suggests that existing adoption models may systematically underestimate the importance of institutional and relational attributes relative to purely technical performance dimensions.

Second, the study advances the literature on algorithmic accountability and AI governance by providing experimental evidence that governance design choices have quantifiably large consequences for technology uptake. This finding reinforces theoretical arguments for embedding governance-by-design principles into AI system development rather than treating governance as an ex-post compliance consideration (Janssen et al., 2020). Third, the study's application of discrete choice experimentation in the AI adoption context demonstrates the methodological value of experimental preference elicitation

relative to cross-sectional survey designs, which are susceptible to common method bias and social desirability effects.

Practical Implications

The findings carry actionable implications for AI-DSS developers, managers, and policymakers. For technology providers, the primacy of governance effects suggests that competitive differentiation in AI-DSS markets may be achieved more effectively through innovative governance design than through marginal improvements in algorithmic accuracy or precision—a counterintuitive but empirically grounded insight. Providers who adopt shared data ownership models may capture adoption premiums that substantially offset the commercial risks associated with relinquishing exclusive data control.

For managers evaluating AI-DSS adoption decisions, the significant cost sensitivity documented in this study implies that total cost of ownership should be carefully assessed against expected productivity gains. Subscription pricing models that impose high fixed costs may face substantial adoption resistance, particularly among cost-sensitive organizational adopters. Finally, for policymakers, the evidence that shared governance structures significantly enhance adoption provides empirical support for regulatory frameworks and industry standards that promote user data rights in AI applications—a policy orientation increasingly reflected in emerging data governance regulation globally.

6. Conclusion

This study set out to examine the determinants of AI-based decision support system adoption by employing a discrete choice experiment design involving 3,823 respondents and 15,292 alternative-level observations. The results of binary logistic regression analysis with cluster-robust standard errors, complemented by average marginal effect estimation, yield three principal findings.

First, cost exerts a statistically significant and substantively meaningful negative effect on AI-DSS adoption, reducing the probability of selection by approximately 0.6 percentage points per unit increase. This finding confirms the role of economic barriers in constraining AI technology uptake and has direct implications for pricing and commercialization strategies in AI product markets.

Second, algorithmic performance attributes—specifically predictive accuracy and spatial precision—do not significantly influence adoption decisions within the range of values examined. This result challenges the assumption that technical superiority is the primary driver of AI-DSS adoption

and suggests that satisficing behavior or attentional limitations may attenuate the adoption-enhancing value of marginal performance improvements.

Third, and most significantly, shared data ownership between the company and the user substantially increases adoption probability by approximately 17 percentage points—an effect that far exceeds those of cost and performance attributes in magnitude. This finding establishes data governance as the dominant driver of AI-DSS adoption in the present experimental context, with profound implications for governance-by-design practices in AI development. Notwithstanding the importance of this result, the absence of a comparable effect for open data governance structures introduces important nuance, suggesting that adoption preferences are maximized under bilateral, controlled data sharing arrangements rather than either unilateral provider control or unrestricted public access.

Taken collectively, the findings of this study advance a governance-centered perspective on AI adoption, in which institutional trust and data sovereignty considerations play a more decisive role than technical performance parameters. This perspective complements and extends existing adoption frameworks by surfacing the relational and governance dimensions of AI-DSS uptake that survey-based attitudinal measures have historically underemphasized.

It is important to acknowledge certain limitations of the present study. The use of a discrete choice experiment with hypothetical alternatives, while methodologically advantageous for causal inference, may not fully capture the behavioral complexity of real-world AI-DSS procurement decisions, which typically involve longer deliberation periods, organizational stakeholder dynamics, and iterative evaluation processes. Additionally, the scope and composition of the respondent sample introduces boundary conditions on the generalizability of findings across industries, organizational sizes, and national contexts. Future research should examine whether the governance primacy effect is robust across diverse organizational settings and whether longer-term experience with AI-DSS moderates the relative salience of governance versus performance attributes in adoption decisions.

Looking forward, this study opens productive avenues for research at the intersection of AI governance, technology acceptance, and experimental economics. Particularly promising directions include the examination of governance transparency mechanisms—such as algorithmic explainability and audit trail provisions—as adoption-relevant attributes alongside data ownership structures. Additionally, longitudinal designs that track adoption behavior over time, as organizational familiarity with AI-DSS grows, would substantially enrich understanding of how governance and cost sensitivities

evolve with technology maturation. In sum, this study contributes both theoretically and methodologically to the scholarly project of understanding how AI governance design shapes the diffusion of artificial intelligence technologies in organizational and operational contexts.

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Artificial intelligence is changing organizations in ways that go far beyond technical innovation. It influences how knowledge is produced, how decisions are supported, how institutional memory is preserved, and how employees prepare for the future of work. These changes bring new opportunities, but they also require careful attention to governance, trust, learning, and human capability.

Artificial Intelligence and Organizational Transformation: Governance, Adoption, and Future Workforce Skills examines these issues through both conceptual discussion and empirical evidence. The book explores organizational learning and unlearning in the age of generative AI, the role of institutional memory in organizational resilience, the relationship between human capital and AI adoption, and the effects of data governance and cost on the adoption of AI-based decision support systems.

Rather than treating artificial intelligence as a simple matter of automation, the book considers how AI becomes part of everyday organizational practice. It shows that successful adoption depends not only on access to technology, but also on the ability to question outputs, protect reliable knowledge, develop workforce skills, design responsible data arrangements, and build institutions that can adapt without losing their judgment.

This book is intended for academics, researchers, managers, policy makers, and professionals who seek to understand how artificial intelligence is reshaping organizations and what kinds of capabilities will be needed in the years ahead. It offers a grounded perspective on AI as both a technological and organizational challenge, reminding readers that the future of work will be shaped not only by what machines can generate, but also by how wisely institutions choose to learn, govern, and act.



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