# From AI Adoption to Organizational Value: A Conceptual Framework of Complementary Capabilities


## Abstract

Artificial intelligence adoption gives organizations access to new computational possibilities, but access does not establish that these possibilities improve organizational outcomes. Existing research connects AI capability with performance and emphasizes the importance of complementary resources. Less explicit is how particular capabilities reinforce one another, where value conversion fails, and why successful task performance may not yield sustained organizational returns. This conceptual paper develops a framework linking AI adoption to organizational value through operational assimilation and process improvement. It integrates selected academic literature published through 2024, using the resource-based view as a foundation, complementarity theory to explain interdependence, and dynamic capabilities to explain renewal. Four complementary capabilities are distinguished: data stewardship and integration, human expertise and AI literacy, workflow redesign and coordination, and responsible AI governance. Resource orchestration connects these capabilities to particular use cases rather than treating them as an undifferentiated maturity score. Eight propositions explain capability interactions, context-specific bottlenecks, the conversion of process gains into retained value, and the conditions under which learning sustains benefits over time. The framework distinguishes complementarity from additive resource accumulation and identifies value capture as a separate problem from technical improvement. It also recognizes transition costs, harmful outcomes, and unsuccessful investments, avoiding the assumption that delayed returns necessarily indicate future success. The paper contributes a conditional process account of AI value realization and outlines experimental, longitudinal, and configurational approaches for future research. Managerial implications concern use-case selection, coordinated capability investment, benefit ownership, and evidence-based decisions about scaling, redesigning, or discontinuing AI applications.



Keywords: artificial intelligence; organizational value; complementary capabilities; resource orchestration; dynamic capabilities; AI assimilation; responsible AI governance.


## 1 Introduction

Artificial intelligence can alter how organizations analyze information, produce content, allocate resources, and make decisions. These possibilities create a strategic question that extends beyond whether an organization adopts an AI application: how does adoption generate value that the organization can realize and sustain? Buying access to an application, running a pilot, and embedding a system in a consequential business process represent different organizational achievements. Treating them as equivalent makes it difficult to explain why apparently similar investments produce different outcomes.

The distinction is established within the broader information systems literature. Bharadwaj (2000) examines information technology capability rather than technology ownership alone,

while Melville et al. (2004) connect IT business value with organizational resources and processes. AI research develops this reasoning further. Mikalef and Gupta (2021) conceptualize AI capability as a configuration of resources and associate it with organizational creativity and performance. Enholm et al. (2022) synthesize the enablers, uses, and value-generating mechanisms of AI. These studies provide a strong basis for investigating the organizational conditions surrounding technology use.

Nevertheless, a capability explanation can remain incomplete if it simply asserts that organizations with more resources perform better. Data, skills, process arrangements, and governance may each contribute to outcomes, but this does not establish that they are complementary. Complementarity requires a stronger claim: the contribution of one capability increases when another relevant capability is present. Moreover, an aggregate capability measure may conceal a decisive weakness. A firm may possess advanced analytical expertise while lacking the authority or coordination needed to act on its outputs. Understanding value realization therefore requires explicit mechanisms connecting particular capability combinations with use and outcomes.

Evidence available before 2025 also cautions against assuming that AI assistance always creates superior performance. Noy and Zhang (2023) report productivity benefits in professional writing tasks, but their experiment does not establish firm-wide financial returns. Vaccaro et al. (2024) distinguish improvement over humans alone from performance relative to the better of humans or AI alone. Their meta-analysis shows why these benchmarks should not be conflated. An organization may improve a familiar work arrangement without selecting the best available arrangement or capturing the resulting benefit.

AI creates additional management challenges because its outputs and operating conditions can change. Berente et al. (2021) identify autonomy, learning, and inscrutability as central management concerns. These features make performance dependent on ongoing interaction among technical systems, organizational routines, and human judgment. An application that performs well during a limited demonstration may become unreliable when inputs change or when its outputs enter a different decision context. The problem is therefore both one of initial deployment and one of continued organizational adaptation.

This paper asks: How do complementary organizational capabilities convert AI adoption into realized organizational value, and under what conditions do these relationships strengthen, weaken, or fail? The proposed answer is a process framework in which adoption enables operational assimilation, assimilation supports process improvement, and process improvement produces organizational value only when benefits are retained and costs and risks remain acceptable. Four capabilities shape this sequence: data stewardship and integration, human expertise and AI literacy, workflow redesign and coordination, and responsible AI governance.

The paper makes three intended contributions. First, it separates adoption, assimilation, process improvement, and organizational value to prevent performance from being inferred from technology use. Second, it specifies complementarity through capability interactions and context-specific bottlenecks rather than assuming that all resources can be combined into an

interchangeable stock. Third, it connects value realization with resource orchestration and dynamic renewal, explaining how coordinated managerial decisions and subsequent learning influence results. These arguments are developed as propositions for future examination, not reported as newly established empirical findings.

# 2 Literature review

## 2.1 AI adoption and organizational assimilation

AI adoption is defined here as an organizational decision to authorize and initiate the use of an AI application in an identified activity. It includes internally developed and externally supplied applications. The definition does not imply widespread use, successful integration, or realized benefits. Operational assimilation refers to repeated use within actual workflows, supported by established responsibilities, reliable access to relevant inputs, and procedures for acting on outputs. An adopted application may remain outside routine work, while an assimilated application may still generate poor outcomes.

This distinction follows the organizational emphasis of research on digital transformation. Vial (2019) presents transformation as involving organizational responses and changes in value creation rather than the presence of digital technologies alone. Orlikowski's (2000) practice perspective similarly directs attention to how technology becomes consequential through recurrent use. The implication for AI is that deployment cannot be understood solely through technical installation or an employee's willingness to try a tool.

The framework applies to predictive and generative applications, while recognizing their different operating requirements. Feuerriegel et al. (2024) discuss generative AI's opportunities and challenges for information systems research. Generative outputs may require validation for factual accuracy, appropriate use, and contextual relevance; predictive outputs require evaluation against their decision purpose and operating conditions. The model does not assume that a capability configuration suitable for one application transfers unchanged to another. The relevant unit is a defined AI use case embedded in a particular organizational process.

## 2.2 From technical performance to organizational value

AI-related outcomes occur at different levels. Technical performance concerns the system's ability to perform its designated task. Process improvement concerns an attributable change in the quality, speed, consistency, or resource requirements of work. Organizational value concerns benefits realized by the organization after considering implementation and operating costs, opportunity costs, and relevant risks. These levels are connected but not interchangeable. A model can predict accurately without changing a decision, and a faster decision can fail to improve the outcome for which the organization is accountable.

Enholm et al. (2022) distinguish value-generating mechanisms and multiple orders of AI effects. The present paper uses that insight to separate proximal process outcomes from broader organizational returns. For example, a hypothetical service organization might reduce drafting

time while increasing review work. Alternatively, a team could free time without having sufficient demand or an alternative use for the capacity. These illustrations show why technical output and local time savings are insufficient measures of realized organizational value.

The meaning of improvement also depends on the comparison. Vaccaro et al. (2024) show that human augmentation and human–AI synergy are different empirical questions. A human–AI arrangement can outperform unaided people while performing worse than AI alone. Conversely, retaining human involvement may be justified by accountability or consequences that a narrow accuracy benchmark excludes. The appropriate comparison must therefore be specified before performance is evaluated, including the non-AI alternative and relevant constraints on acceptable action.

### 2.3 Resource-based explanations of AI capability

The resource-based view explains performance differences through heterogeneity in organizational resources and the conditions under which they support competitive advantage (Barney, 1991). In information systems research, Wade and Hulland (2004) clarify how the perspective can be applied to organizational technology resources. These arguments suggest that widely available AI applications do not automatically constitute distinctive strategic assets. Their value can depend on how they are combined with organization-specific information, expertise, relationships, and routines.

Mikalef and Gupta (2021) operationalize a broader AI capability construct and provide evidence linking it with creativity and performance. Their contribution makes it inappropriate to present the general proposition that AI requires complementary organizational resources as wholly new. The present paper instead develops a narrower question: which interactions make resources productive in a particular use case, and how are the resulting gains converted into outcomes at organizational level? This shifts attention from the possession of an overall capability to the mechanisms through which capabilities jointly operate.

A capability is defined here as a repeatable organizational ability to mobilize resources for an identifiable function. Having a dataset is a resource condition; maintaining its suitability for operational decisions is a capability. Employing specialists is not identical to coordinating their knowledge with frontline expertise. This distinction also limits circularity: capabilities must be identifiable through routines and practices independently of whether the AI project ultimately succeeds.

### 2.4 Human expertise and the organization of AI-assisted work

Human–AI research examines how analytical and contextual contributions can be combined. Jarrahi (2018) discusses human–AI symbiosis in organizational decision making, while Dellermann et al. (2019) develop the concept of hybrid intelligence. These perspectives motivate attention to task allocation and interaction rather than a simple opposition between people and machines. They do not establish that every task benefits from collaboration or that adding a human reviewer always improves results.

Shrestha et al. (2019) examine organizational decision-making structures in the presence of AI, linking system characteristics with arrangements for decision authority. Raisch and Krakowski (2021) argue that automation and augmentation are interdependent and can create tensions over time. Together, these contributions indicate that organizational value depends partly on how responsibilities are redistributed, how exceptions are handled, and how decision rights change as AI use develops.

Faraj et al. (2018) examine the organizational implications of learning algorithms. A related concern is that gains at one level can generate costs elsewhere. Doshi and Hauser (2024), studying creative writing, find individual creativity benefits alongside reduced collective diversity of content. Their result should not be generalized into a universal organizational effect, but it demonstrates why one favorable metric cannot represent every dimension of value. Portfolio-level novelty, workload distribution, and capability development may require separate assessment.

### 2.5 Governance, learning, and resource orchestration

AI governance concerns the arrangements through which organizations allocate responsibility, specify acceptable uses, evaluate risks, and respond to failures. Papagiannidis et al. (2023) examine governance practices, barriers, and outcomes through comparative cases. Their work places governance within organizational implementation rather than outside it as a final approval formality. The framework developed here treats governance as an operating capability whose contribution depends on its proportionality and connection to actual use.

Learning also matters because access to external knowledge does not establish the ability to apply it. Cohen and Levinthal (1990) explain absorptive capacity as an organizational ability related to recognizing, assimilating, and applying external knowledge. Zahra and George (2002) distinguish dimensions concerned with potential and realized absorptive capacity. Applied to AI, this literature suggests that obtaining a new tool or training material is different from converting its lessons into revised work practices.

Resource orchestration provides the managerial connection among capabilities. Sirmon et al. (2007) focus on how resources are managed to create value, while Sirmon et al. (2011) develop orchestration across organizational breadth, depth, and life cycle. The implication is that capability investments require decisions about sequencing, bundling, and deployment. The present framework uses orchestration as a coordinating mechanism; it does not treat it as another resource to be added mechanically to a maturity index.

## 3 Theoretical lens

### 3.1 Resource-based view as the foundation

The resource-based view explains why access to comparable technologies can coexist with different organizational outcomes. Its role in this paper is to identify the organizational assets and abilities surrounding AI use. A purchased application can be shared across competitors,

whereas complementary routines and contextual knowledge may be more difficult to reproduce. However, distinctiveness alone does not establish that a capability is valuable. Its contribution must be assessed relative to a task, alternative arrangements, and the cost of maintaining it.

The paper therefore uses the resource-based view without defining capability through performance. Data stewardship, human expertise, workflow redesign, and governance can be observed through their practices before returns are known. Competitive advantage is also separated from organizational value: an investment can improve performance without outperforming rivals, and a temporary advantage can disappear as competitors adapt. These distinctions follow the analytical discipline needed when applying resource explanations to information systems (Wade & Hulland, 2004).

### 3.2 Complementarity theory as the explanation of interaction

Milgrom and Roberts (1995) explain organizational fit through complementarities among choices. The essential idea is that doing more of one activity increases the return from doing more of another. In this paper, complementarity is a proposition about the joint effect of particular capabilities, not a synonym for their general usefulness. Human expertise and workflow redesign, for example, are complementary when the benefit of improved expertise is larger under a workflow that allows people to act on and challenge AI outputs.

Let V(h,w | z) denote expected value for a fixed use case, where h and w indicate lower or higher levels of human expertise and workflow redesign and z represents other specified conditions. A local complementarity claim is:

$$V(1,1 \mid z) - V(0,1 \mid z) > V(1,0 \mid z) - V(0,0 \mid z)$$

The inequality compares the value of a joint upgrade with the separate upgrades. It is a conceptual restriction to be tested, not an estimated result. The capabilities can each have positive individual effects while failing this test. The relationship may also reverse where additional coordination imposes more cost than benefit. Complementarity is consequently local to an application, capability range, and organizational context; universal positive interaction among every capability pair is not assumed.

The framework additionally distinguishes complementarity from a bottleneck. A bottleneck exists where one inadequate capability prevents an application from meeting a required operating condition. A minimum data-quality requirement may be necessary for a particular prediction task even if the smooth interaction between data and expertise has not been established. Both concepts explain why additive capability scores may mislead, but they imply different empirical tests and managerial responses.

### 3.3 Dynamic capabilities as the explanation of renewal

Teece et al. (1997) explain the integration and reconfiguration of competences in changing environments. Teece (2007) further develops sensing, seizing, and reconfiguring as foundations of dynamic capabilities. Their role here is to explain how an initially useful combination remains

appropriate as tasks, data, applications, and stakeholder requirements change. A capability configuration can lose relevance even when its components remain individually strong.

The paper distinguishes ordinary operating capabilities from dynamic capabilities. Maintaining a current data pipeline or reviewing outputs according to a stable procedure supports present operations. Detecting that the procedure no longer fits the task and reorganizing the arrangement concerns renewal. This distinction prevents every improvement activity from being classified as dynamic. Evidence of renewal requires changes in the capability configuration or operating model rather than continued execution of an existing routine.

### 3.4 Integrated theoretical argument

The three perspectives address different questions. The resource-based view identifies relevant organizational differences; complementarity theory explains why some differences are more productive together; dynamic capabilities explain revision of the configuration over time. Resource orchestration connects these explanations with concrete managerial action. It concerns identifying the use case, selecting and sequencing investments, coordinating responsibilities, and redeploying resources when evidence changes.

The integrated argument is that AI adoption enables possibilities whose realization depends on an appropriate capability configuration. The configuration supports assimilation into work; assimilation can improve processes; and those improvements create organizational value when the organization retains benefits exceeding relevant costs while meeting its obligations. Subsequent learning can revise any part of this chain. Failure at one stage cannot be diagnosed reliably through a single measure of AI adoption intensity or aggregate technological sophistication.

## 4 Methodology

### 4.1 Conceptual research design

The paper uses a theory-synthesis design with model development, supported by a purposive integrative literature review. Jaakkola (2020) explains the importance of an explicit conceptual research design and distinguishes approaches including theory synthesis and model development. Torraco (2005) describes critical integration as a means of generating new perspectives. The present paper combines these approaches to formulate relationships among capabilities and value-conversion stages. It does not report primary data collection, a statistical estimation, or a new meta-analysis.

### 4.2 Evidence identification and publication boundary

The selected evidence base comprises 30 academic publications dated 1990–2024. The cutoff is 31 December 2024. Final issue publication years are used where an article appeared online earlier; publications assigned to 2025 or later are excluded. Targeted scholarly web searches located publisher records, scholarly repository entries, accessible texts, and abstracts. Searches addressed AI capability and business value, human–AI collaboration, organizational decision-

making, governance, productivity, complementary investments, resource orchestration, and the foundational theories.

The search strategy was purposive and concept-led. Broad searches on AI capability and value were supplemented by targeted searches for studies that clarified interactions, competing outcomes, and theoretical mechanisms. Academic publisher and author records supported bibliographic checking. Detailed interpretations were restricted to what accessible abstracts or texts supported. The study did not undertake a comprehensive bibliographic database export, an independently replicated screening exercise, or a PRISMA selection procedure. The 30 references therefore constitute the selected foundation of the argument rather than an exhaustive mapping of the field.

### 4.3 Selection and analytical procedure

Publications were retained when they performed at least one of four functions: defining AI or organizational capability; explaining technology-related value creation; illuminating capability interdependence and organizational adaptation; or providing conceptual research guidance. Preference was given to peer-reviewed research and established theoretical contributions. Unverified vendor claims, future publications, and general commentary without an identifiable analytical role were excluded. Evidence from bounded tasks was used to qualify assumptions, without treating it as direct proof of organizational-level effects.

The synthesis followed four analytical steps. First, it separated technology adoption from use and outcomes. Second, it compared how selected studies explained data, people, process arrangements, governance, and learning. Third, it mapped these explanations to the resource-based, complementarity, and dynamic-capability perspectives. Fourth, it developed propositions and considered rival explanations, including direct technical effects, managerial selection, and organizational size. These steps describe conceptual reasoning, not a coded dataset or frequency-based thematic analysis. Snyder (2019) provides methodological support for making the review's purpose and boundaries explicit.

### 4.4 Standards of conceptual rigor

The framework is evaluated through construct clarity, consistency of mechanisms, scope conditions, and falsifiability. Capabilities are defined independently of realized value to reduce tautology. Adoption, assimilation, improvement, and value are separated to avoid measuring the same outcome under different labels. Complementarity claims specify interactions rather than relying on positive correlations among capabilities. The propositions also allow failure, substitution, and negative outcomes, making them open to empirical contradiction.

The review remains limited by selective coverage and uneven access to full texts. It does not claim thematic saturation, intercoder agreement, publication-bias correction, or a numerical estimate of any proposed effect. Its contribution is an integrated explanation and a set of testable expectations. The evidence needed to validate the framework is discussed in the research agenda.

# 5 Conceptual analysis and proposition development

## 5.1 Components and levels of the framework

The proposed framework contains an enabling decision, four ordinary capability domains, a coordinating mechanism, and a sequence of outcomes. AI adoption is the enabling decision. Data stewardship, human expertise, workflow redesign, and governance provide the capability domains. Resource orchestration coordinates their development and deployment. Operational assimilation and process improvement form the principal value-conversion sequence, while benefit retention, costs, and acceptable risk determine realized organizational value. Dynamic renewal connects later observations with revised configurations.

| Capability | Organizational function | Example practices | Failure addressed |
|---|---|---|---|
| Data stewardship and integration | Maintain suitable information and access | Source ownership; provenance; consistent definitions; operating connections | Unsuitable inputs and unreliable access |
| Human expertise and AI literacy | Interpret outputs and exercise relevant judgment | Domain-specific learning; error recognition; exception handling | Uncritical acceptance or ineffective use |
| Workflow redesign and coordination | Reorganize work to make outputs actionable | Task allocation; handoffs; decision rights; benefit ownership | Isolated outputs and displaced work |
| Responsible AI governance | Keep use accountable and proportionate to consequences | Use boundaries; monitoring; escalation; incident response | Unmanaged harm and unreliable scaling |

*Table 1. Complementary capabilities and their distinct organizational functions. Examples describe proposed observable practices rather than validated measurement scales.*

The use case is the focal unit for explaining interactions. Capabilities may reside at team, business-unit, or enterprise level, but their relevance must be connected to the same application. Firm-wide value is an aggregate outcome and cannot be inferred merely by averaging users' perceptions of local convenience. This multilevel distinction is especially important where an AI application shifts work or cost from one department to another.

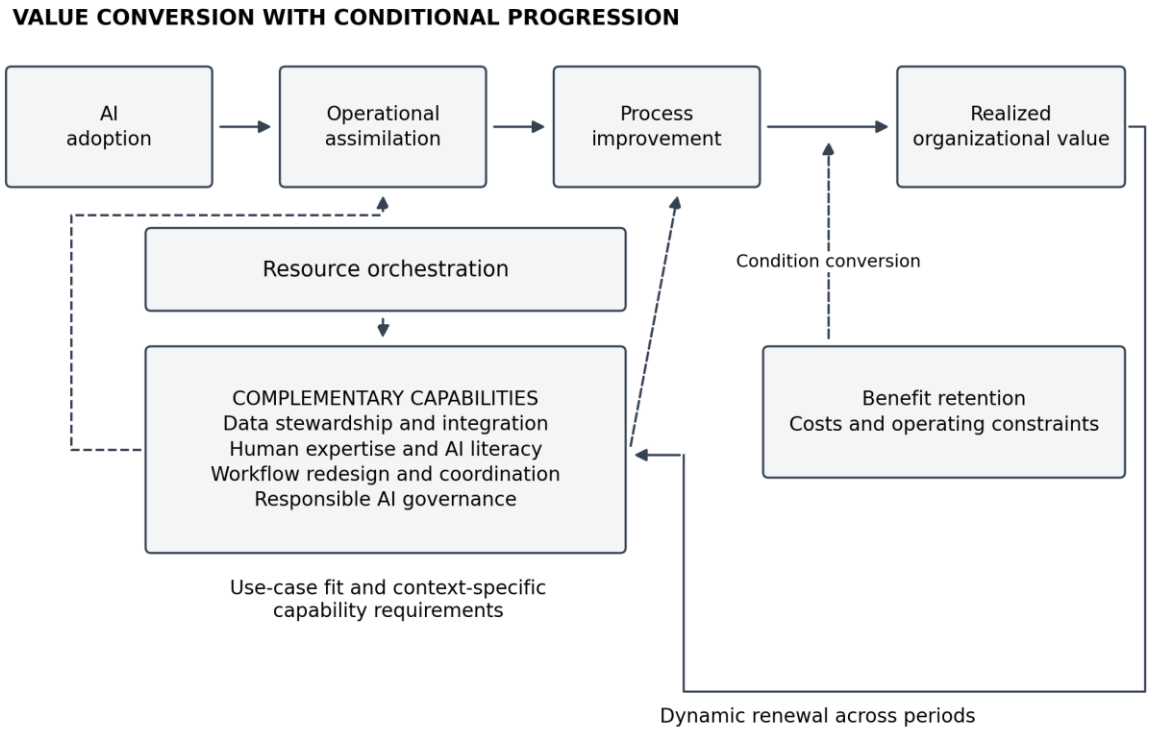


*Figure 1. Proposed framework of AI adoption and organizational value. Solid arrows represent the proposed value-conversion sequence. Dashed arrows indicate conditioning or coordination. The return path represents renewal across periods rather than same-period causality. Adoption permits but does not guarantee progression.*

### 5.2 Data stewardship as a condition of operational assimilation

Data stewardship and integration capability is the ability to maintain suitable, accessible, and interpretable information for a specified AI use case. It includes ownership, provenance, appropriate access, consistent definitions, and connections with operating systems. The relevant capability concerns fitness for purpose rather than data volume. A large repository may be unsuitable if its records do not represent the task, if permissions prevent use, or if updates do not reach the application when needed.

This capability supports the transition from an authorized pilot to repeated operational use. The mechanism is reduced friction between the application and the process it serves. Reliable access and shared definitions allow outputs to be generated and interpreted consistently. Weaknesses produce workarounds, delayed decisions, or exceptions that prevent routine use. This is a theoretical extension from the resource emphasis of AI capability research, rather than a finding established for every AI application (Mikalef & Gupta, 2021).

The proposition does not assume that every organization must train its own model. A purchased generative application may require little internal training data yet still depend on retrieval documents, access controls, and evidence for output validation. Accordingly, relevance is defined through the information dependencies of the use case, not through a universal requirement for extensive proprietary datasets.

**Proposition 1.** *The positive relationship between AI adoption and operational assimilation is stronger when data stewardship and integration capability meets the information requirements of the focal use case.*

### 5.3 Human expertise and workflow redesign as complementary capabilities

Human expertise and AI literacy capability is the ability to interpret outputs, recognize task limitations, combine domain knowledge with computational assistance, and exercise appropriate judgment. Workflow redesign and coordination capability is the ability to reorganize tasks, handoffs, decision rights, and performance expectations around an application. The first concerns what organizational participants can understand and do; the second concerns whether the work arrangement enables those contributions.

The proposed complementarity arises because knowledgeable employees need opportunities and authority to act on their knowledge. Training may have limited value if workloads encourage uncritical acceptance or if users cannot challenge unsuitable outputs. Conversely, redesigned processes may fail when participants cannot recognize errors or interpret recommendations. Joint improvement is expected to reduce these mutually reinforcing constraints, producing more reliable assimilation than either investment alone.

This interaction is conditional on the role assigned to people. The human–AI literature supplies reasons to examine joint task design, but it does not establish collaboration as universally superior (Jarrahi, 2018; Dellermann et al., 2019). Fully automating a bounded task may require different operating expertise and exception handling than collaborative decision-making. The capability definition therefore concerns appropriate human contribution, including supervision and redesign, rather than a requirement that every output receive manual review.

**Proposition 2.** *For AI use cases requiring material human interpretation or exception handling, human expertise and workflow redesign are complementary: their joint improvement produces a greater increase in operational assimilation than the sum of their separate improvements, within the relevant capability range.*

### 5.4 Governance and the reliable scaling of AI use

Responsible AI governance capability is the ability to assign accountability, specify acceptable uses, evaluate consequential errors, manage incidents, and revise or withdraw applications. Its effectiveness depends on functioning procedures and decision authority, not simply the existence of a written policy. Governance differs from data stewardship because it concerns the acceptability and accountability of the overall application; data stewardship concerns the information on which the application depends.

At limited scale, informal oversight may conceal unresolved responsibility. Expansion increases the number of decisions, affected parties, and opportunities for error propagation. Proportionate governance is expected to improve the reliability of this expansion through clear review thresholds, escalation routes, and monitoring. This argument builds on the organizational

management concerns identified by Berente et al. (2021) and the governance practices examined by Papagiannidis et al. (2023).

Governance also consumes resources and can delay legitimate uses. Its contribution is therefore evaluated over the relevant operating horizon and relative to risk exposure. The proposition concerns governance matched to consequences and uncertainty, not maximal control. In a low-consequence drafting task, intensive approval at every step may destroy time savings; in a consequential decision, insufficient oversight may make apparent efficiency unacceptable.

**Proposition 3.** *As operational assimilation expands, proportionate AI governance strengthens its contribution to reliable process improvement, with the expected benefit increasing with the consequences and propagation potential of AI errors.*

### 5.5 Context-specific bottlenecks and resource orchestration

Capability complementarity does not imply that organizations should maximize every capability simultaneously. A use case may be constrained by one operational requirement while other capabilities are already adequate. For example, additional model expertise will not resolve a decision-rights problem if nobody has authority to change the process. Equally, reorganizing a workflow cannot make an application suitable when its outputs remain too unreliable for that task.

Resource orchestration directs attention to the constraint rather than the largest visible investment. The managerial activity is to identify a material weakness, coordinate the investments that address it, and evaluate whether the resulting arrangement supports the intended process. This connects the resource-management reasoning of Sirmon et al. (2007, 2011) with the local interdependence emphasized by complementarity theory. The bottleneck need not remain fixed: resolving an information constraint can make coordination the next limiting condition.

The claim is narrower than saying that the lowest capability score always determines performance. Minimum requirements depend on task characteristics, accessible substitutes, and the organization's ability to obtain external support. Outsourcing can resolve a technical constraint without eliminating the need to evaluate suppliers or accept accountability. A meaningful bottleneck must be identified through the operating requirements of the application, not inferred retrospectively from a project's failure.

**Proposition 4.** *When a specific complementary capability is below a use-case requirement and lacks an adequate substitute, investment that resolves that bottleneck produces greater assimilation improvement than an equivalent investment in a capability already above its required level.*

### 5.6 Assimilation, process improvement, and value retention

Assimilation provides a route for AI outputs to affect actual work, but repeated use does not prove improvement. An application can be routinely used because it is mandated or convenient

while lowering quality. Improvement requires a defensible comparison with the relevant alternative, including work transferred to reviewers, users, or other departments. Shrestha et al. (2019) highlight the importance of decision structures, supporting attention to how outputs become organizational action.

Even established improvement leaves a value-retention problem. Time saved may be redeployed productively, used to increase service quality, or remain idle. Revenue benefits may be offset by supplier charges, implementation costs, or competitive price reductions. These are proposed mechanisms through which process gains can fail to become retained organizational returns; they are not additional results inferred from task experiments. Noy and Zhang's (2023) evidence is useful precisely because its task-specific scope should remain distinct from these wider claims.

Organizational value is assessed as an attributable profile rather than an unrestricted financial score. Cost efficiency, service quality, innovation, and resilience may require separate indicators. Legal obligations and unacceptable harms can impose constraints that should not be treated as freely exchangeable with savings. An organization that creates private returns while transferring material harm to employees or customers has not thereby established socially beneficial value. The framework requires these outcomes to remain visible.

**Proposition 5.** *AI adoption contributes to realized organizational value through operational assimilation and attributable process improvement, but the conversion of improvement into retained value depends on benefit ownership, productive use of released capacity, and the costs and constraints of the chosen operating arrangement.*

### 5.7 Renewal and the persistence of benefits

An effective initial configuration can become unsuitable as data, tasks, applications, or organizational goals change. Dynamic renewal is the ability to detect these changes and revise the operating arrangement. It can include narrowing an application's role, revising retrieval sources, changing review responsibilities, switching suppliers, or discontinuing a use case. Renewal is not defined as increasing AI use; withdrawing an unsuitable application can protect value.

The mechanism is correction of declining fit before the decline overwhelms the benefits of assimilation. Absorptive-capacity research helps explain why exposure to new knowledge is insufficient without its organizational application (Cohen & Levinthal, 1990; Zahra & George, 2002). The proposed extension concerns learning from operational evidence: participants must be able to turn identified failures and successes into revised routines and investments rather than simply reporting them.

Feedback can itself be misleading when outcomes are delayed, review practices change, or AI recommendations influence the data later used to assess the system. The framework therefore proposes renewal through relevant and independently checked indicators where feasible. It does not assume that the collection of more feedback automatically improves a system or that continuous retraining is always the appropriate response.

**Proposition 6.** *Under changing task or operating conditions, dynamic renewal weakens the decline in AI-related process benefits by enabling evidence-based revision of the complementary capability configuration.*

### 5.8 Investment timing and contingent value trajectories

Capability development creates transition costs before benefits are fully realized. Employees learn unfamiliar practices, teams run parallel processes, and managers redesign responsibilities. Brynjolfsson et al. (2021) explain how intangible investments associated with general-purpose technologies can contribute to a productivity J-curve and complicate measurement. Their account motivates attention to timing, but it does not establish that every AI implementation must follow the same trajectory.

The framework distinguishes delayed realization from permanent failure. An early decline is consistent with investment in useful complements, but it is also consistent with poor use-case selection or continuing technical inadequacy. A defensible temporal argument requires observable evidence that the relevant constraint is being reduced. Falling costs of verification, improved quality under a stable benchmark, or successful integration may justify continued investment; recurring use without such improvement may not.

Similarly, strong early task gains can be temporary. Scaling may expose new coordination costs or reveal that downstream demand limits the productive use of saved capacity. The expected time path therefore depends on the capability-building burden and the organization's ability to retain benefits. Patience alone is not a capability and should not substitute for evaluation.

**Proposition 7.** *Where realizing AI value requires substantial complementary investment, early net returns are lower than later returns only if subsequent assimilation, process improvement, and benefit retention occur; without those transitions, longer adoption duration does not imply higher realized value.*

### 5.9 Task fit and alternative capability configurations

The relative contribution of capabilities varies across tasks. A stable, easily verified task with inexpensive errors can support a different arrangement from a novel task whose quality is difficult to judge and whose mistakes have serious consequences. This variation concerns the requirements of the use case rather than a simple classification of predictive AI as low risk or generative AI as high risk. Both application types can be used in settings with different consequences.

Raisch and Krakowski (2021) explain why automation and augmentation cannot be separated neatly across time. The framework nevertheless treats the allocation of tasks as an empirical design choice. Human expertise, decision authority, and verification should be organized around the comparative strengths and limitations of the arrangement. Evidence of human augmentation alone cannot determine that humans and AI together provide the best feasible solution, as the benchmarking distinction in Vaccaro et al. (2024) demonstrates.

The expected result is multiple workable configurations rather than one universal maturity ladder. Some organizations can obtain technical services externally while investing internally in domain expertise and coordination. Others may require stronger internal technical resources because their tasks or data cannot be supported adequately through external services. The model predicts configuration differences subject to adequate operating conditions; it does not predict that every possible combination can succeed.

**Proposition 8.** *The capability configuration producing the greatest realized value varies with task uncertainty, output verifiability, error consequences, and access to substitutes; no single allocation of human involvement, workflow integration, and governance is optimal across all AI use cases.*

# 6 Discussion

## 6.1 Theoretical contribution

The framework develops a conditional explanation of the movement from AI adoption to organizational value. Its contribution is not the general claim that technology needs organizational complements, which is well established. The more specific contribution is to connect distinct conversion stages with identifiable interactions and failure conditions. This permits explanations of an authorized application that never becomes routine, a routine application that fails to improve work, and an improved process whose gains are not retained by the organization.

A second contribution is to distinguish resource accumulation from complementarity and bottlenecks. Positive relationships among data capability, expertise, and performance are insufficient evidence that the capabilities reinforce one another. The proposed interaction requires a joint gain beyond separate improvements. A bottleneck claim instead concerns a use-case requirement that cannot be offset adequately by other resources. Separating these explanations makes the framework more demanding and provides clearer guidance for empirical tests.

A third contribution concerns the location of managerial action. Orchestration is the activity through which managers select applications, coordinate investments, resolve constraints, and decide whether to scale or withdraw. Dynamic renewal concerns revision when the operating environment changes. These activities can overlap in practice, but their analytical roles differ: orchestration concerns deploying a configuration; renewal concerns changing its basis of fit. This distinction avoids treating every favorable managerial practice as another independent predictor.

The framework also qualifies the meaning of organizational value. Gains for an individual worker, a team, and an organization can diverge. Increased individual output may raise verification demands elsewhere, while common suggestions can influence the diversity of an organization's output. Doshi and Hauser (2024) offer a bounded demonstration of individual and collective outcomes moving differently. The conceptual implication is to assess portfolios of

outcomes and their distribution, rather than substituting a single local productivity measure for organizational success.

### 6.2 Rival explanations and limits to generalization

Several alternatives could explain observed associations between capabilities and AI-related value. Better-managed organizations may be more likely both to develop capabilities and to select promising use cases. Organizational size may provide funding and bargaining power that improve returns independently of a particular interaction. Prior digital infrastructure may explain both assimilation and performance. These alternatives require research designs that establish timing and compare credible alternatives, rather than relying exclusively on contemporaneous managerial assessments.

Reverse causality is also plausible. A successful application can finance training, governance, and data improvements, creating the appearance that these capabilities preceded the benefits. Failed applications may disappear from samples, exaggerating the observed value of long-term adoption. Researchers should retain discontinued projects and record capability changes before outcomes where possible. A duration–performance association among surviving projects cannot by itself support Proposition 7.

The model does not imply that AI is preferable to all simpler alternatives. Rule-based automation, search tools, staff development, or process simplification may provide equivalent benefits at lower cost. Nor does it imply that specialized capabilities always need to be owned internally. External services can substitute for some resources, but their adequacy depends on integration, information access, and organizational responsibility. Comparative analysis should therefore examine the chosen arrangement against feasible alternatives rather than only against absence of AI.

### 6.3 Managerial implications

Managers should begin with a process problem and an explicit comparison. The use case should specify the intended decision or work output, the acceptable error profile, the affected groups, and the non-AI alternative. This makes it possible to select relevant measures before enthusiasm for a technology defines success. Benefits should be assessed at the point where work becomes consequential, including review and correction rather than only the initial production of an output.

Capability investment should follow an assessment of dependencies and constraints. If data access prevents reliable use, additional user training will not resolve the main problem. If outputs are reliable but decision rights remain unclear, more model development may add little value. A staged investment approach should identify which complementary changes are required together and which can be postponed. The framework provides a rationale for such diagnosis; it does not supply universal spending ratios.

Human responsibilities need operational clarity. Employees should understand when to use an application, when to question it, and who can change the process after repeated errors. Training

should be connected with opportunities to exercise judgment and with sufficient time for verification. Where manual review adds no demonstrated benefit, managers should reconsider its design rather than assuming that human presence provides effective oversight. Where consequences are serious, apparent speed gains should not displace required accountability.

Value ownership should be assigned beyond the implementation team. A process owner should explain how released capacity will be used and how quality or service gains will be retained. Cost assessment should include procurement, integration, monitoring, correction, training, and transition burdens without double counting the same expense. Different outcome dimensions should remain visible where they cannot defensibly be combined. These arrangements make it easier to distinguish a successful demonstration from a sustainable operating improvement.

Finally, scaling decisions should depend on evidence of fit. A pilot can justify expansion when it performs under relevant conditions and when the complementary capabilities can support greater use. Continued investment should be reconsidered when the identified bottleneck persists or when external alternatives become superior. The capacity to discontinue an unsuitable application is a form of disciplined resource allocation, not evidence that the organization has failed to adopt AI adequately.

### 6.4 Implications for smaller organizations and public services

For smaller organizations, complementary capability development may depend on external provision, shared expertise, and selective application choice. The framework does not require a large internal AI department. It requires access to capabilities adequate for the use case and clarity about who remains accountable. Research should examine the affordability and reliability of such arrangements rather than classifying all small firms as immature on a scale designed for large enterprises.

For public and nonprofit organizations, retained value can take the form of service reliability, accessibility, mission achievement, or resilience. Financial savings remain relevant but are insufficient measures of success. Error consequences and the distribution of gains across affected groups may be central. These settings are conceptual extensions of the framework; they require measures aligned with organizational purpose and should not be assumed to operate through identical commercial value-capture mechanisms.

## 7 Future research and limitations

### 7.1 Research agenda and empirical designs

The most direct test of complementarity would independently vary relevant capability interventions. A field or laboratory study could compare task-specific training, workflow redesign, both interventions, and neither while holding access to the AI application constant. The joint improvement should exceed the sum of separate improvements to support Proposition 2. Researchers should report the comparison on an interpretable outcome scale and account for

intervention costs. A significant association between a broad capability score and performance would not provide the same test.

Longitudinal studies should follow applications from authorization through routine use, process outcomes, and retained value. Data should include unsuccessful and discontinued cases, changes in capability configurations, and the timing of complementary investments. Useful comparisons could involve phased implementation, matched non-adopting processes, or credible natural experiments where their assumptions are justified. These designs would help distinguish delayed benefits, selection, learning, and persistent failure without assuming that every early decline is a J-curve.

Multilevel measurement is needed where enterprise capabilities support team applications. Adoption records can identify authorization and access; use logs and process documents can capture assimilation; independent quality assessments and operational records can evaluate process outcomes. Financial or mission-related indicators should then measure organizational benefits over a relevant horizon. Self-reported success and capability measures from the same respondent can be informative but should not be the sole basis for causal conclusions.

Configurational analysis could examine alternative combinations under clearly defined task conditions. Such work should avoid assuming that a fuzzy-set configuration establishes statistical complementarity or that a necessary condition is equivalent to a positive interaction. These are different claims. Comparative case research can identify candidate mechanisms and bottlenecks, while intervention and longitudinal designs can test their effects. A combined research program would be more informative than selecting an analytical method solely because the framework contains multiple capabilities.

### 7.2 Construct development and limitations

Future measurement should preserve the separation between an ability and its realized outcome. Workflow redesign capability should capture the organization's capacity to change work arrangements; assimilation should capture whether the focal application is embedded in those arrangements. Governance capability should capture functioning accountability and response practices rather than policy presence alone. Dynamic renewal should capture revision following changed conditions, while ordinary monitoring remains part of ongoing operation. These distinctions require validation before an aggregate instrument is proposed.

The paper has several limitations. Its purposive review cannot establish exhaustive coverage, prevalence, or effect sizes. It draws on literatures developed across different technologies and contexts, so extending older information systems arguments to AI requires direct testing. Some applications may create value through immediate technical substitution with relatively limited organizational change, making the proposed mediated sequence less central. The framework also simplifies tensions among different stakeholder outcomes and cannot determine which harms or obligations are acceptable in every setting.

The publication boundary excludes research published from 2025 onward. The framework therefore integrates predictive and generative AI evidence available through 2024 without claiming to describe subsequent technological or organizational developments. Its propositions identify expected mechanisms and conditions rather than deterministic outcomes. Their usefulness depends on whether future empirical research can distinguish genuine capability interactions from general organizational quality and establish when the proposed value-conversion stages matter.

## 8 Conclusion

AI adoption creates opportunities whose organizational value depends on how work, resources, and accountability are arranged. This paper develops a framework connecting adoption with operational assimilation, process improvement, and retained value through four complementary capabilities. The resource-based view identifies organizational differences, complementarity theory explains interactions, and dynamic capabilities explain continued adaptation. Eight propositions specify how information requirements, human expertise, workflow redesign, governance, bottlenecks, value retention, timing, and task conditions influence the conversion process. The central argument is that effective AI management requires evidence about capability fit and realized outcomes rather than treating adoption intensity as success. Testing this argument requires comparisons that preserve the distinction between better technical output, improved organizational processes, and value that an organization can responsibly sustain.

## References


Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly, 45*(3), 1433–1450. https://doi.org/10.25300/MISQ/2021/16274

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly, 24*(1), 169–196. https://doi.org/10.2307/3250983

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics, 13*(1), 333–372. https://doi.org/10.1257/mac.20180386

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152. https://doi.org/10.2307/2393553

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering, 61*(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2

Doshi, A. R., & Hauser, O. P. (2024). Generative AI enhances individual creativity but reduces the collective diversity of novel content. *Science Advances, 10*(28), Article eadn5290. https://doi.org/10.1126/sciadv.adn5290

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers, 24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering, 66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Jaakkola, E. (2020). Designing conceptual articles: Four approaches. *AMS Review, 10*(1–2), 18–26. https://doi.org/10.1007/s13162-020-00161-0

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly, 28*(2), 283–322. https://doi.org/10.2307/25148636

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

Milgrom, P., & Roberts, J. (1995). Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics, 19*(2–3), 179–208. https://doi.org/10.1016/0165-4101(94)00382-F

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187–192. https://doi.org/10.1126/science.adh2586

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. Organization *Science, 11*(4), 404–428. https://doi.org/10.1287/orsc.11.4.404.14600

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI governance: Identifying best practices and potential barriers and outcomes. *Information Systems Frontiers, 25*(1), 123–141. https://doi.org/10.1007/s10796-022-10251-y

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83. https://doi.org/10.1177/0008125619862257

Sirmon, D. G., Hitt, M. A., & Ireland, R. D. (2007). Managing firm resources in dynamic environments to create value: Looking inside the black box. *Academy of Management Review, 32*(1), 273–292. https://doi.org/10.5465/amr.2007.23466005

Sirmon, D. G., Hitt, M. A., Ireland, R. D., & Gilbert, B. A. (2011). Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. *Journal of Management, 37*(5), 1390–1412. https://doi.org/10.1177/0149206310385695

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review, 4*(3), 356–367. https://doi.org/10.1177/1534484305278283

Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. *Nature Human Behaviour, 8*(12), 2293–2303. https://doi.org/10.1038/s41562-024-02024-1

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems, 28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Wade, M., & Hulland, J. (2004). Review: The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS Quarterly, 28*(1), 107–142. https://doi.org/10.2307/25148626

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review, 27*(2), 185–203. https://doi.org/10.5465/amr.2002.6587995