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Why Organizations Fail Before AI Fails: A Process Theory of Organizational Internalization, Enabling Governance, and AI Survivability

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Abstract

Technical operation is a weak test of whether artificial intelligence (AI) has become an organizational capability. An AI system can remain accurate, available, and institutionally visible while its outputs lose influence over routines, decision rights, and managerial judgment. Yet existing research on adoption, implementation, AI capability, and risk governance offers limited insight into why technically sound AI systems may gradually lose organizational consequence after deployment. This conceptual paper locates that problem in organizational internalization. It distinguishes technical implementation from operational, structural, and cognitive embedding and develops Organizational AI Survivability as the continuity of an AI-supported capability under disruption. Enabling governance links models to routines, accountability, interpretation, and learning; cumulative governance realignment explains how those links are repaired across successive episodes of leadership change, restructuring, regulatory change, and model drift. Five propositions organize the argument as a temporal sequence from embedding to continuity or fragility. The resulting process theory shifts explanation away from deployment as an endpoint and toward the governance work through which organizations repeatedly reproduce accountable alignment. It offers bounded constructs, observable mechanisms, and longitudinal research designs for examining why organizations sometimes lose an AI-supported capability while the underlying technology continues to operate.

Keywords: Artificial intelligence; Organizational internalization; Enabling governance; AI survivability; Cumulative governance realignment; Organizational capabilities.

1. Introduction

Implementation is no longer the most revealing threshold in organizational AI. Firms and public agencies routinely place models inside credit decisions, maintenance schedules, compliance reviews, service allocation, and managerial dashboards. The harder question begins after deployment: whether these systems continue to shape action when personnel, data, regulation, or strategy changes. A technically successful installation can therefore coexist with a capability that is already losing organizational force.

The paradox is visible in the distance between technical presence and organizational consequence. A model may continue producing outputs while users work around it, accountability migrates elsewhere, exceptions cease to inform redesign, or managers can no longer explain when its recommendations should govern a decision. Dashboards and formal committees may survive this erosion. What disappears is the patterned reliance that turns a technical system into an organizational capability.

Prior research explains several parts of this trajectory. AI capability studies identify the resources, data infrastructure, and skills associated with performance (Mikalef and Gupta, 2021; Berente et al., 2021). Digital transformation research connects digital technologies to structural change and strategic renewal (Vial, 2019), while managerial accounts document implementation across organizational settings (Davenport and Ronanki, 2018). Responsible AI governance adds structural, relational, and procedural practices for accountability and lifecycle oversight (Papagiannidis, Mikalef and Conboy, 2025). These literatures clarify acquisition, use, and control; none makes the continued organizational viability of a specific AI-supported capability its primary outcome.

The harder question is what happens when the organization around a deployed model starts to change. Leadership turnover can change interpretive priorities; restructuring can split decision authority; regulatory change can invalidate established review routines; and model drift can expose gaps between technical monitoring and operational response. To explain continuity under these conditions, we need to examine whether routines, accountability, interpretation, and learning stay connected—rather than assuming implementation is a stable endpoint.

The research question is therefore precise: under what organizational conditions does a technically implemented AI system remain a viable capability through successive disruptions? Failure, in this formulation, need not begin with model breakdown. It begins when reliance becomes ceremonial, decision responsibility becomes ambiguous, feedback no longer changes practice, or institutional memory of the system's limits is lost. The organization can fail to sustain the capability before the technology fails to run.

Digital implementation without organizational internalization names this condition. It describes an AI system that is deployed and symbolically legitimate but only weakly connected to recurrent work, formal responsibility, and shared interpretation. Investment and executive sponsorship may persist even as operational use fragments and the system becomes easier to abandon or misuse.

Enabling governance addresses the work required to prevent or repair that separation. Control, compliance, and risk limitation remain necessary, but they do not by themselves connect technical evidence to operating decisions. Enabling arrangements bring technical, operational, legal, and managerial actors into repeated contact; allocate responsibility for AI-supported decisions; preserve feedback; and authorize revision when conditions change. Governance is enabling to the extent that it maintains accountable use while allowing the surrounding capability to learn.

Four contributions follow. The argument treats AI survivability—not deployment—as the outcome to be explained; separates adoption, implementation, and internalization; identifies enabling governance as post-implementation alignment work; and connects weak internalization to fragmented accountability and declining institutional reliability. These claims are developed as a process theory rather than as a list of implementation factors.

1.1 Research Positioning and Framework Development Approach

The study uses conceptual theory building to explain organizational AI survivability after implementation. Its evidence base is theoretical rather than statistical: concepts and mechanisms are developed by comparing work on AI governance, institutionalization, routines, dynamic capabilities, resilience, and information systems implementation.

Comparative conceptual analysis was used to identify where these traditions converge and where their explanatory objects differ. The analysis focused on the interval after technical deployment, especially disruptions that unsettle established links among models, work practices, decision authority, interpretation, and learning.

The result is a bounded process model whose propositions specify what later qualitative, longitudinal, and quantitative studies must observe: layered embedding, governance episodes, disrupted alignment, and continuity of a particular AI-supported capability over time.

1.2 Concept Development Procedure

The conceptual framework was developed through a structured synthesis of four complementary literature streams: AI governance, institutional theory, routine dynamics, and digital transformation research. The development process followed three iterative analytical stages.

First, key mechanisms related to AI implementation, organizational adaptation, governance, and institutional reproduction were identified across existing literature. Second, these perspectives were critically compared to examine their ability to explain why some AI initiatives become embedded organizational capabilities while others remain temporary technical interventions. Third, insights from these theoretical domains were integrated into developing four interconnected concepts: organizational internalization, enabling governance, cumulative governance realignment, and AI survivability.

The objective of this process was not to generate a new theory from empirical observation, but to extend existing theoretical explanations by integrating fragmented perspectives into a coherent framework explaining the organizational conditions that support sustained AI capability.

2. Theoretical Problem: From Implementation Success to Organizational Survivability

2.1 The technology-centric trap

AI research has generated substantial knowledge about deployment conditions, data capabilities, analytical sophistication, and organizational readiness. However, these explanations often assume that successful implementation naturally progresses toward sustained organizational value. Such an assumption overlooks a critical distinction: deploying an AI system does not necessarily mean that the organization has developed the capacity to sustain it.

Implementation represents the technical and operational availability of an AI system, whereas organizational internalization refers to the deeper process through which AI becomes embedded within routines, governance arrangements, managerial interpretation, roles, and organizational memory. Although adoption initiates technological transformation, internalization determines whether AI becomes a durable organizational capability.

This distinction exposes a technology-centric limitation in current AI research. Organizations may successfully implement AI while failing to redesign the structures and practices required to preserve its relevance over time. Consequently, the central challenge is not merely how organizations introduce AI, but how they maintain AI as an organizationally meaningful and sustainable capability.

2.2 Why Existing Perspectives Are Insufficient for Explaining AI Survivability

Several theoretical perspectives—institutional theory, dynamic capabilities, routine dynamics, sociomaterial approaches, and recent AI governance frameworks—offer valuable but partial explanations of technological change and organizational adaptation. However, none specifically addresses the post-implementation problem of how a particular AI-supported capability retains accountable decision rights, interpretive continuity, and recurrent use across successive organizational disruptions.

Table 1 synthesizes these limitations and contrasts them with the extensions proposed by the present framework.

Theoretical Perspective / Literature Stream	Established Explanatory Strength	Gap in Explaining AI Survivability	Framework-Specific Extension
Institutional Theory & AI Adoption Literature	Explains legitimacy, isomorphism, symbolic adoption, and decoupling between formal structures and practice.	Does not specify how alignment around an AI capability is deliberately repaired after disruption (e.g., leadership turnover, regulatory change).	Organizational Internalization identifies operational, structural, and cognitive embedding; Cumulative Governance Realignment explains deliberate alignment repair.
Dynamic Capabilities & AI Capability Research	Explain how organizations sense change, seize opportunities, and reconfigure resources.	Explains strategic adaptation but does not isolate the governance work that preserves accountable alignment around a specific AI capability during reconfiguration.	Enabling Governance maintains decision rights, interpretive continuity, coordination, and learning during change. Its outcome is accountable alignment, not resource reconfiguration itself.
Routine Dynamics & Digital Transformation Research	Explains endogenous stability and change through recurrent action and strategic renewal.	Does not explain who maintains cross-routine responsibility when AI-supported practices become fragmented or overridden.	Cumulative Governance Realignment connects routine adaptation to accountability, feedback, and institutional memory across disruption episodes.
Sociomaterial / Practice Perspectives & Responsible AI Governance	Explain the mutual constitution of technology and organizing through use; address risk control, compliance, and lifecycle oversight.	Offer limited explanation of how governance intentionally regenerates coherence across leadership, regulatory, or structural discontinuities.	AI Survivability explains how governance repeatedly restores coherence between technical functioning and organizational reliance, preserving trust and accountability over time.

Sharpening the Boundary: Enabling Governance as Distinct from Dynamic Capabilities

A critical conceptual boundary requires explicit attention: the distinction between Enabling Governance and Dynamic Capabilities (Teece, 2007). Dynamic capabilities explain an enterprise-level capacity to sense environmental shifts, seize opportunities, and reconfigure broad resource bases (Teece, Pisano and Shuen, 1997). Their explanatory target is strategic renewal at the organizational level. Enabling governance, in contrast, addresses a narrower post-implementation problem: the preservation and restoration of accountable decision rights, interpretive continuity, and learning feedback attached to a *specific* AI-supported capability during organizational change.

An organization may exercise dynamic capabilities by reallocating capital or restructuring divisions, while simultaneously allowing a focal AI capability to undergo progressive cognitive and structural decoupling. Enabling governance does not aim at general resource renewal; its singular outcome is the regeneration of accountable organizational alignment between a deployed model and its surrounding work practices, routines, and accountability structures. Consequently, enabling governance functions as a domain-specific enabler that supports the micro-foundations of capability retention, rather than serving as a relabeled dynamic capability or a generic compliance mechanism.

The limitation of existing perspectives, then, is not that they are incorrect. It is that each holds a different part of the post-implementation problem in view while leaving the full disruption–response sequence under-specified. Institutional theory explains legitimacy and decoupling; routine and sociomaterial perspectives explain enactment; dynamic capabilities explain reconfiguration; and AI governance explains oversight. None alone derives how a specific AI-supported capability moves from embedding, through disrupted alignment, to governance-enabled repair and renewed continuity. That sequence is the explanatory object of the present process theory. Rather than replacing these perspectives, the framework integrates their complementary insights to address a specific unresolved question: why do some AI initiatives become enduring organizational capabilities while others remain technically functional but organizationally fragile?

2.3 Extending Resilience Thinking Toward AI Survivability

Organizational resilience research provides an additional foundation for understanding durability under uncertainty. Resilience perspectives explain how organizations anticipate, absorb, respond to, and learn from disruption (Sutcliffe and Vogus, 2003; Lengnick-Hall, Beck and Lengnick-Hall, 2011; Williams et al., 2017; Duchek, 2020). Strategic resilience further emphasizes renewal and adaptation before environmental pressures generate organizational decline (Hamel and Valikangas, 2003). Similarly, management research conceptualizes resilience as a multi-level capability involving continuity, adaptation, and transformation (Bhamra, Dani and Burnard, 2011; Annarelli and Nonino, 2016; Linnenluecke, 2017; Hillmann and Guenther, 2021).

These perspectives establish an important premise: durability is not passive persistence but an active capability to preserve coherence, regenerate capacity, and adapt under changing conditions.

However, AI survivability represents a more specific organizational challenge than general resilience. The object requiring continuity is not the organization as a whole, but an AI-enabled capability embedded within routines, accountability structures, interpretive processes, and learning mechanisms. An organization may demonstrate resilience while allowing a specific AI capability to deteriorate. Likewise, an AI system may remain technically operational while organizational capacity to interpret, govern, and rely on that system gradually declines.

AI survivability focuses resilience thinking on the specific problem of keeping alignment around a particular AI capability. Availability alone is insufficient; the relevant question is whether the institutional conditions that keep AI meaningful, governable, and valuable persist or can be restored.

Table 2. Why Existing Theories Do Not Fully Explain AI Survivability

Theoretical perspective	Established explanatory strength	Unresolved post-implementation problem	Framework-specific extension
Institutional theory	Legitimacy, isomorphism, symbolic adoption, and decoupling	Does not specify how alignment around an AI capability is deliberately repaired after disruption	Organizational internalization identifies operational, structural, and cognitive embedding; cumulative governance realignment explains alignment repair
Dynamic capabilities	Sensing, seizing, and reconfiguring resources under change	Explains strategic adaptation and resource reconfiguration, but does not isolate the governance work that preserves accountable alignment around a specific AI capability after implementation	Enabling governance maintains decision rights, interpretive continuity, coordination, and learning during change; its outcome is accountable alignment, not resource reconfiguration itself
Routine dynamics	Endogenous stability and change through recurrent action	Does not explain who maintains cross-routine responsibility when AI-supported practices become fragmented	Cumulative governance realignment connects routine adaptation to accountability, feedback, and institutional memory
Sociomaterial and practice perspectives	Mutual constitution of technology and organizing through use	Offers limited explanation of intentional governance regeneration across leadership, regulatory, or structural discontinuities	AI survivability explains how governance repeatedly restores coherence between technical functioning and organizational reliance

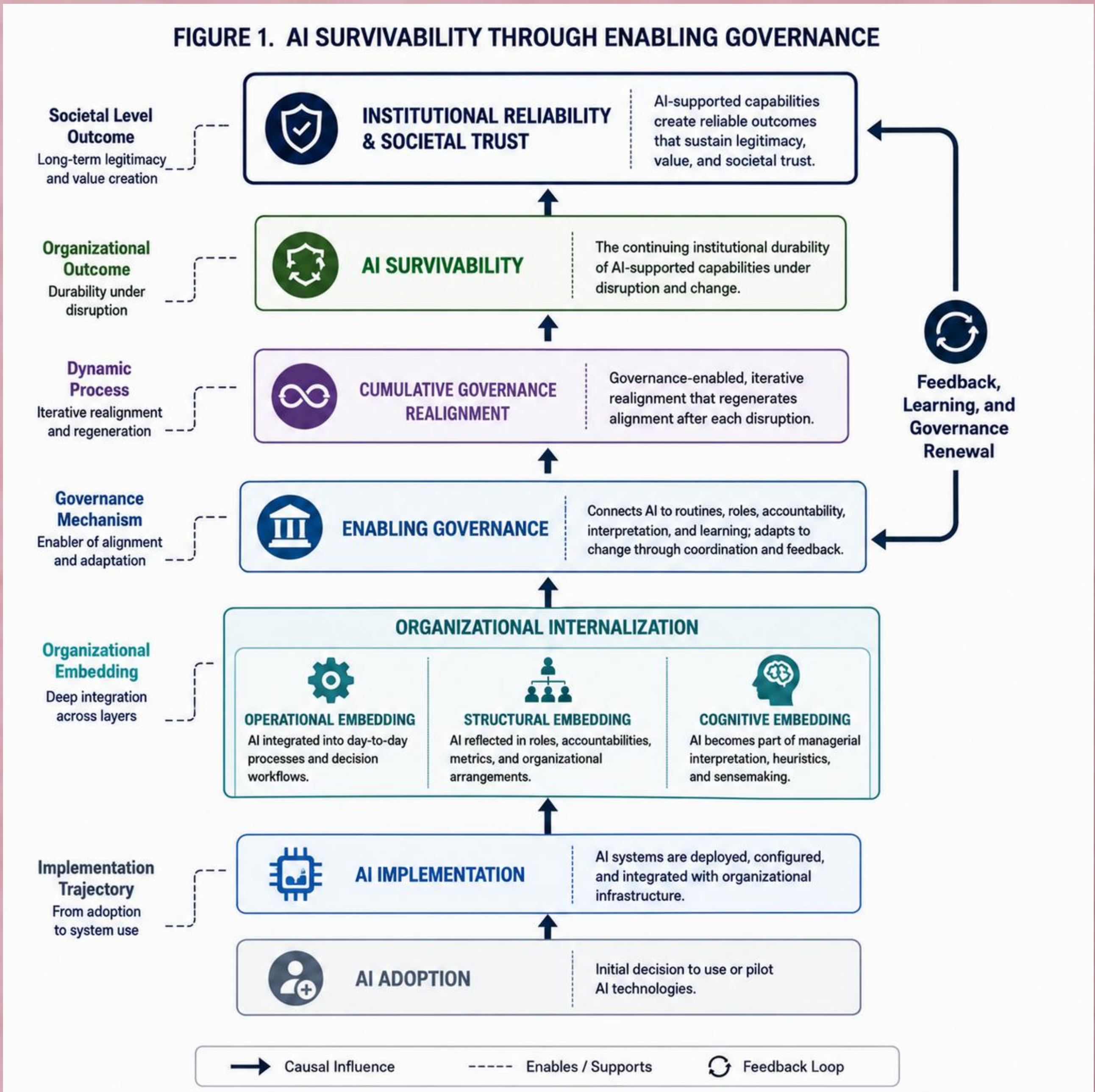

Figure 1 illustrates the central logic of the framework. AI adoption and implementation initiate technological deployment, but organizational survivability emerges only when AI becomes operationally, structurally, and cognitively embedded. Enabling governance sustains this process through repeated cycles of cumulative governance realignment that regenerate alignment among AI systems, routines, accountability structures, managerial interpretation, and organizational learning. Sustained alignment ultimately supports organizational durability, institutional reliability, and societal trust in AI-supported decisions.

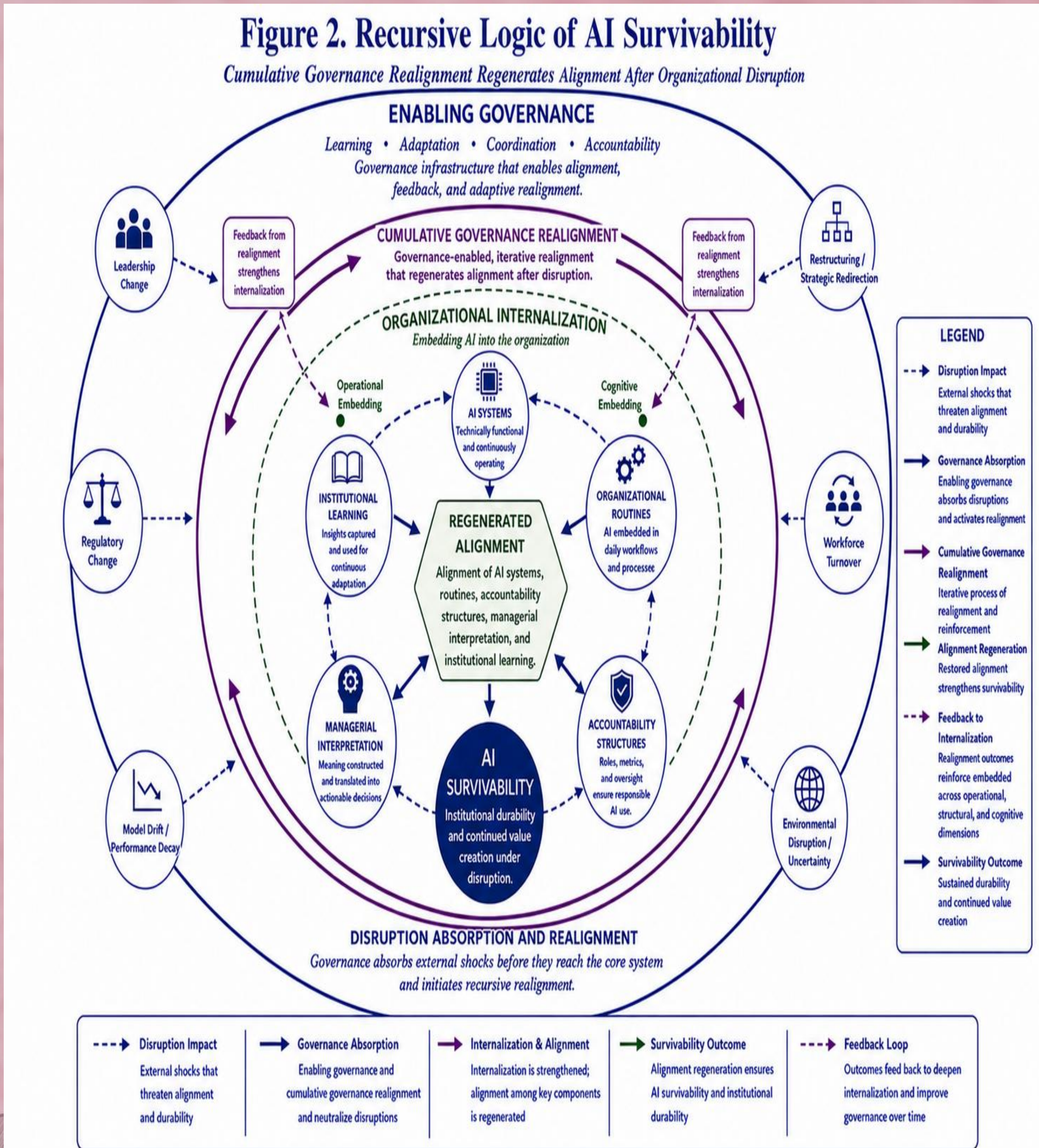

Figure 2. Recursive Logic of AI Survivability

Cumulative Governance Realignment Regenerates Alignment After Organizational Disruption

and routines	decoupling, routines, organizational reproduction	routines, governance, and cognition remain aligned over time	governance realignment and layered embedding

3. Core Concepts

3.1 Digital Implementation without Organizational Internalization

Digital implementation without organizational internalization describes a condition in which AI systems are deployed, funded, technically functional, and strategically recognized, yet remain insufficiently embedded within organizational routines, structures, accountability arrangements, and interpretive practices. The concept does not refer to technological failure or unsuccessful deployment. Rather, it captures a situation where implementation appears successful at the technical level while organizational durability remains uncertain.

This condition may emerge when AI capabilities remain concentrated within specialized technical units, when AI outputs are not incorporated into recurring decision processes, when responsibility for AI-supported decisions remains unclear, or when managerial actors continue to rely primarily on established judgment practices despite formal AI adoption. In these circumstances, AI exists within the organization but has not become fully integrated into the organizational systems through which decisions, learning, and accountability are reproduced.

3.2 Organizational Internalization

Organizational internalization refers to the process through which AI becomes embedded within the operational, structural, and cognitive architecture of an organization. Unlike adoption, which concerns acceptance and initial use, and implementation, which concerns technical deployment and operational availability, internalization concerns whether AI becomes integrated into the ways organizations coordinate activities, make decisions, learn, and maintain accountability over time.

Internalization is an ongoing process of embedding rather than a capability or a single implementation outcome. Its observable result is a degree and configuration of embeddedness across operational, structural, and cognitive dimensions. This distinction permits researchers to study internalization as change over time while measuring the depth of embeddedness achieved at a particular point.

3.3 Enabling Governance

Enabling governance extends traditional oversight by actively supporting the conditions under which AI-supported capabilities can endure. It performs four interdependent functions: routine alignment, accountability allocation, interpretive coordination, and learning integration. Routine alignment connects model outputs to recurring operational workflows. Accountability allocation clarifies who holds decision rights and bears responsibility when AI informs or drives outcomes. Interpretive coordination enables shared understanding of model strengths, limitations, and appropriate use. Learning integration ensures that exceptions, overrides, and performance deviations feed back into both technical refinement and organizational practice. Weakness in any one dimension can weaken internalization even when the remaining functions are well developed. Their joint operation provides a more robust foundation for internalization and survivability than any single function in isolation. These functions are further elaborated in Section 4.2, where we examine their role as embedding mechanisms.

4. Conceptual Framework: AI Survivability through Enabling Governance

The process model links technical deployment to organizational survivability through three mechanisms: layered embedding, enabling governance, and the repeated regeneration of alignment. Its logic is temporal: a capability is formed through internalization and tested whenever disruption unsettles the relationships on which that internalization depends.

The five propositions specify a temporal process sequence rather than independent covariance claims. Proposition 1 explains capability formation through layered embedding. Proposition 2 identifies the governance capacity that deepens and maintains that embedding. Proposition 3 begins when disruption unsettles an internalized capability and governance episodes attempt to restore alignment. Proposition 4 explains how the residue of earlier episodes accumulates in revised routines, decision rights, controls, and institutional memory, conditioning later continuity. Proposition 5 specifies the failure pathway when governance restricts action without converting disruption into organizational learning and repair. The sequence is therefore formation → governance enablement → disruption and repair → cross-episode accumulation → continuity or fragility.

4.1 Layered Embedding

AI becomes organizationally internalized through three interconnected dimensions.

Operational embedding occurs when AI becomes integrated into recurring workflows, reporting processes, tasks, and decision activities.

Structural embedding occurs when accountability arrangements, governance mechanisms, reporting relationships, and evaluation systems incorporate AI-supported practices.

Cognitive embedding occurs when managers and organizational members develop shared interpretations regarding AI-supported judgment, learning, coordination, and responsibility.

Embedding within one dimension alone may produce incomplete internalization. Operational integration without structural support may create dependency without accountability. Structural integration without cognitive acceptance may produce formal compliance without meaningful use. Cognitive support without operational integration may result in positive perceptions without sustained practice.

No single embedding dimension is sufficient. Operational use without accountable ownership is brittle; formal ownership without recurrent use is ceremonial; and both weaken when managers lack a shared interpretation of the system's role and limits.

Proposition 1:

AI initiatives are more likely to develop into organizational capabilities when operational, structural, and cognitive embedding are jointly present; weakness in any one-dimension limits organizational internalization.

4.2 Enabling Governance as the Embedding Mechanism

As defined in Section 3.3, enabling governance performs four continuity functions—routine alignment, accountability allocation, interpretive coordination, and learning integration. Rather than reapplying the definition here, we focus on how these functions operate as embedding mechanisms that connect AI to organizational routines, responsibilities, and learning processes.

Examples of enabling governance include cross-functional AI governance structures involving technical, managerial, legal, risk, and operational actors; roles that translate AI outputs into organizational meaning; post-implementation reviews focused on learning and adaptation; and feedback processes that capture errors, exceptions, and contextual changes.

These mechanisms highlight the sociotechnical nature of AI survivability. Technical performance and organizational alignment influence each other continuously. Weak organizational engagement may accelerate performance decline through reduced feedback and adaptation, while declining technical reliability may weaken trust and organizational reliance.

Proposition 2:

Enabling governance deepens organizational internalization by aligning routines, allocating decision accountability, coordinating interpretation, and integrating feedback into organizational learning.

4.3 Cumulative Governance Realignment

Cumulative governance realignment is a temporal process mechanism through which repeated governance episodes restore and progressively renew alignment among AI systems, organizational routines, decision rights, managerial interpretation, and institutional learning. It operates within the broader theory of Organizational AI Survivability by explaining how alignment is regenerated after disruption rather than assumed to persist automatically.

Unlike perspectives that view implementation as a completed event, this concept emphasizes that AI durability requires continuous organizational maintenance. As organizations experience leadership changes, restructuring, regulatory developments, or environmental uncertainty, governance mechanisms repeatedly restore alignment between AI capabilities and organizational needs.

AI survivability therefore emerges not from a single successful implementation decision, but from recurring cycles of adjustment, interpretation, learning, and governance renewal.

Proposition 3:

When disruption unsettles an internalized AI-supported capability, survivability is more likely when governance episodes restore alignment among AI systems, routines, decision rights, managerial interpretation, and organizational learning.

Table 4. Conceptual Boundaries of the Framework Constructs

Construct	Theoretical Meaning	Organizational Role	Conceptual Boundary
Organizational Internalization	A formation process through which AI becomes operationally, structurally, and cognitively embedded; its observable result is a degree and configuration of embeddedness	Transforms deployment into an integrated organizational capability	A process, not a capability; distinct from adoption, acceptance, and technical implementation
Enabling Governance	An organizational governance capacity comprising routine alignment, accountability	Maintains accountable alignment and supports	A governance capacity and condition, not a resource-reconfiguration

	allocation, interpretive coordination, and learning integration	internalization before and after disruption	capability or compliance structure alone
Cumulative Governance Realignment	A temporal process mechanism through which successive governance episodes restore alignment and leave changes that condition later responses	Explains disruption-triggered repair and cross-episode accumulation	A temporal mechanism, not a capability, statistical mediator, or generic account of recursion
AI Survivability	The capability-level continuity of meaningful, accountable, interpretable, and adaptable AI-supported use under disruption	Represents the outcome explained by the process theory	An outcome, not technical reliability, availability, sustainability in general, or short-term performance

These conceptual distinctions establish analytical boundaries among the framework's central constructs and clarify how each construct contributes a distinct explanatory role in understanding organizational AI survivability.

4.3.1 Mechanisms of Accumulation and Reinforcement

When leadership changes, structures are redrawn, regulations shift, or models drift, previously established connections weaken. Organizations then draw on enabling governance to diagnose these gaps and reconnect the relevant elements. Each successful episode leaves organizational traces: revised routines, clarified responsibilities, updated interpretive frames, or strengthened feedback mechanisms. These traces are not neutral; they shape the organization's capacity to respond to future disruptions by creating precedents, embedding new roles, and altering expectations about who decides what. This cumulative character distinguishes realignment from isolated fixes and explains how Organizational AI Survivability is maintained over time rather than restored afresh after each disruption.

4.3.2 Governance Reinforcement and Internalization Continuity

Organizational internalization provides the foundation through which AI becomes embedded across operational, structural, and cognitive dimensions. However, such embedding cannot be assumed to remain stable after implementation. Under conditions of leadership transition, restructuring, regulatory change, workforce movement, and environmental uncertainty, governance becomes important in maintaining alignment and preserving internalization continuity.

Enabling governance supports this continuity by maintaining accountability arrangements, strengthening organizational learning, and renewing feedback mechanisms that connect AI systems with evolving organizational needs.

Proposition 4:

The capacity to preserve organizational internalization across successive disruptions increases when the outcomes of prior realignment episodes are retained in revised routines, decision rights, controls, and institutional memory.

4.4 Restrictive Governance and Organizational Fragility

In contrast to enabling governance (Section 3.3), governance that remains primarily restrictive, detached from organizational practice, or symbolic may achieve formal control while failing to support meaningful AI internalization. Organizations may satisfy compliance expectations while leaving routines unchanged, accountability unclear, and managerial interpretation underdeveloped.

Under these conditions, AI may remain technically operational but organizationally fragile. The system exists, but the organizational capacity required to rely on, interpret, and adapt it gradually weakens.

Proposition 5:

When governance remains primarily restrictive and fails to translate disruption into revised routines, responsibilities, interpretation, and learning, AI-supported capabilities are more likely to undergo progressive organizational decoupling and fragility.

Table 5. Conceptual Dimensions of Organizational AI Internalization

Diagnostic Dimension	Guiding Question
Operational Embedding	Are AI outputs incorporated into routine organizational decisions?
Structural Embedding	How are responsibilities assigned when AI contributes to organizational decisions?
Cognitive Embedding	Do organizational actors understand how AI changes decision processes?
Governance Configuration	Does governance enable organizational learning from AI use?
AI Survivability	Can AI-supported capabilities remain meaningful during disruption?

5. Illustrative Applications of the Framework

The following applications are presented as conceptual illustrations rather than empirical case studies or validation evidence. Their purpose is to demonstrate how the proposed mechanisms may operate across different organizational contexts and to clarify the explanatory value of the framework.

These illustrations draw on recurring themes identified in research on AI implementation, digital transformation, algorithmic decision-making, and organizational adaptation. They do not represent empirical tests of the framework; rather, they provide contextual examples of how organizational internalization, enabling governance, cumulative governance realignment, and AI survivability may interact in practice.

5.1 Financial Services: AI in Credit and Risk Assessment

Financial organizations increasingly use AI to support credit scoring, fraud detection, and risk assessment. However, technical capability alone does not guarantee organizational durability. An AI-supported risk system may generate accurate predictions while remaining weakly internalized if credit officers perceive outputs as external recommendations, accountability for AI-informed decisions remains unclear, or governance focuses primarily on model approval and compliance documentation.

From the perspective of the proposed framework, survivability depends on whether governance mechanisms connect AI outputs with credit policies, escalation procedures, human oversight practices, and organizational learning processes. Through enabling governance, AI becomes integrated into risk decision routines rather than operating as a separate analytical function.

This example illustrates the distinction between technical continuity and organizational survivability. A credit-scoring model may continue functioning while losing organizational influence if trust, accountability, and feedback mechanisms deteriorate. Conversely, organizations that maintain governance-supported learning cycles can continuously reconnect AI outputs with decision processes and institutional knowledge.

In financial settings, durability depends on more than predictive performance. Credit policy, escalation rules, human review, and model feedback must remain aligned as risk conditions and regulatory expectations change.

5.2 Industrial Operations: AI in Predictive Operational Management

Industrial organizations often deploy AI for predictive maintenance, operational planning, and process optimization. Although these systems may provide valuable predictions, their long-term contribution depends on whether operational routines, maintenance practices, incentives, and accountability structures adapt around AI-supported decision processes.

Within the proposed framework, enabling governance provides the mechanism through which technical predictions become organizationally meaningful. Feedback between AI systems, operational teams, performance evaluation, and decision routines allows organizations to continuously adjust their use of AI when conditions change.

This perspective highlights why technically accurate predictive systems may still become fragile during workforce changes, restructuring, supply-chain disruption, or strategic shifts. The challenge is not maintaining algorithmic availability alone, but preserving the organizational relationships that allow AI recommendations to influence practice.

AI survivability therefore emerges through repeated governance-enabled alignment among technical capabilities, operational routines, and organizational learning processes.

5.3 Public Governance: AI in Audit and Compliance Systems

Public organizations increasingly explore AI-supported systems for audit, compliance, and oversight activities. However, technical deployment does not automatically produce institutional value. When governance remains limited to procedural compliance, AI may generate reports and recommendations without becoming integrated into accountability practices, institutional learning, or administrative decision processes.

Public-sector survivability places particular weight on traceable responsibility and contestable interpretation. AI outputs must remain connected to oversight roles, review procedures, reasons that can be communicated, and public accountability as institutional conditions change.

This issue is particularly important in public contexts where legitimacy and trust depend not only on technological performance but also on transparency, accountability, and consistent interpretation. AI-supported systems remain institutionally durable when organizations continuously renew alignment between technological capability and public responsibility.

5.4 A Documented Illustration: Zillow Offers

The 2021 unwinding of Zillow Offers provides a diagnostic illustration of digital implementation without organizational internalization (Zillow Group, 2021). This illustration does not constitute an empirical test of the framework, nor can public disclosures definitively establish the absence of organizational internalization. Nevertheless, viewed through the lens of the present theory, the collapse reflects a structural decoupling between predictive modeling and operational execution across the three embedding dimensions:

- **Operational Embedding Misalignment:** While the Neural Zestimate algorithm was technically operational and integrated into pricing pipelines, operational routines failed to adapt. Purchasing workflows executed algorithmic price outputs at scale without incorporating operational feedback regarding regional housing volatility and real-time inventory capacity constraints.
- **Structural Embedding Deficit:** Decision rights and risk limits were inadequately distributed. Governance arrangements failed to allocate explicit authority to operational managers to override, recalibrate, or halt algorithmically triggered purchasing commitments when market conditions drifted from the model's training assumptions.
- **Cognitive Embedding Breakdown:** A sharp interpretive disconnect emerged between data science teams evaluating model precision and senior management interpreting market exposure. Managers treated algorithmic forecasts as deterministic valuation bounds rather than probabilistic estimates, leading to capital misallocation and significant inventory write-downs.

From the framework's perspective, Zillow Offers highlights how a high-performing analytical deployment remains organizationally fragile when enabling governance fails to establish recursive feedback loops between model predictions, operating routines, and balance-sheet exposure. The case thus clarifies the diagnostic relevance of the framework without implying that a single instance validates its broader theoretical claims.

6. Discussion: Why Organizations Fail Before AI Fails

Implementation-centered accounts leave one paradox unresolved: a system can remain technically available after it has ceased to function as an organizational capability. "Organizations fail before AI fails" names this divergence. It becomes visible when routines stop incorporating outputs, responsibility becomes ambiguous, feedback no longer changes practice, or managerial interpretation detaches from the conditions under which the system was designed.

6.1 Failure as Organizational Decoupling

Post-implementation failure is better understood as progressive decoupling than as a single breakdown. Operational, structural, and cognitive embedding can erode at different rates. A model may remain inside a workflow while accountability weakens; formal governance may persist after users stop trusting or interpreting outputs; executive sponsorship may outlast the learning mechanisms needed to revise practice. Conventional implementation indicators can therefore remain positive while the capability becomes fragile.

This interpretation changes the relevant outcome. Accuracy, availability, adoption intensity, and short-term performance remain important, but none is sufficient to demonstrate survivability. The stronger criterion is whether the organization can preserve meaningful reliance, accountable use, interpretive competence, and adaptive learning when conditions change.

6.2 Survivability as a Temporal Accomplishment

AI survivability is inherently temporal. Internalization achieved at one point does not guarantee continuity because leadership turnover, restructuring, regulatory change, data drift, workforce movement, and strategic redirection can reopen previously settled relationships. Survivability therefore varies across episodes of disruption and cannot be inferred from a cross-sectional observation of technical use.

This temporal logic clarifies why cumulative governance realignment cannot be reduced to a one-time intervention. Governance responses accumulate: reviews alter responsibilities, exceptions reshape routines, feedback modifies interpretation, and revised controls influence later learning. The analytical focus is the ordered sequence through which prior governance responses condition the organization’s capacity to restore alignment after subsequent disruption.

6.3 Governance as Regenerative Capacity

When governance performs its four enabling functions—alignment, accountability, interpretation, and learning (Section 3.3)—it can regenerate alignment without relinquishing accountability. Restrictive controls may prevent clearly unacceptable actions, but regeneration requires additional governance work: timely cross-functional interpretation, effective escalation pathways, revision of decision rights, preservation of institutional memory, and feedback mechanisms that modify both the technology and the surrounding organizational practices.

Agentic AI systems—those executing complex workflows with limited human intervention—introduce new governance pressures. Unlike traditional analytical tools, these systems compress the time available for human oversight and generate emergent decision paths that are difficult to map onto established managerial heuristics. In our view, this creates two distinct pressures: first, cognitive embedding becomes fragile because managers cannot easily trace how algorithmic trajectories translate into operational choices; second, accountability allocation becomes ambiguous as authority effectively migrates from explicit human authorization to autonomous system actions. The practical implication is that governance must shift from periodic oversight to continuous monitoring of both outputs and decision processes—a transition that many organizations are not yet prepared to make.

This creates a persistent design challenge. Governance positioned too far from operations risks failing to detect emerging misalignments until they become costly. Governance absorbed too deeply into operations may lose the distance necessary for independent judgment. The relevant question is therefore not whether to choose proximity or independence, but how to structure review, escalation, and feedback processes so that governance can learn from practice while remaining capable of challenging it.

7. Societal Implications

Non-internalization becomes a societal issue when AI-supported decisions allocate credit, public services, educational opportunities, healthcare attention, infrastructure maintenance, or regulatory scrutiny. In these settings, organizational continuity affects people who cannot inspect the model or repair the routines surrounding it.

A technically operational system can still generate institutionally fragile decisions. The decisive capacity is not output production but the organization’s ability to explain the basis of use, identify who may override or accept a recommendation, learn from exceptions, and remain answerable as conditions change.

Weak internalization fragments these responsibilities. Ethical principles, technical safeguards, and formal compliance cannot compensate indefinitely for missing ownership, dormant feedback, or depleted interpretive competence. Responsible AI therefore depends on organizational arrangements that preserve transparency, learning, and accountability throughout use.

Trust, on this account, is an organizational achievement as well as a property attributed to an algorithm.

8. Theoretical Contributions

Five bounded contributions follow; each tied to a different explanatory limitation.

First, it introduces Organizational AI Survivability as an outcome distinct from adoption, implementation success, technical continuity, and organization-level resilience. Its object is the continued organizational viability of a specific AI-supported capability.

Second, it specifies organizational internalization as the formation process through which deployment becomes operationally, structurally, and cognitively embedded. Institutional theory explains legitimacy and decoupling, while technology research explains acceptance and implementation; internalization explains how continued organizational reliance is formed without treating embeddedness itself as a capability.

Third, it extends AI governance research by identifying an enabling function that complements control, ethics, and compliance. Enabling governance explains how accountability, coordination, interpretation, and learning are actively maintained after deployment.

Fourth, cumulative governance realignment contributes a temporal process mechanism that is more specific than general accounts of recursive adaptation. It explains how repeated governance episodes reconnect AI systems with routines, decision rights, feedback, and institutional memory, and how the residue of each episode conditions the next. Its theoretical role is therefore to explain the regeneration of accountable alignment within the broader process theory of Organizational AI Survivability.

Fifth, the framework establishes a multilevel explanation of durability. Technical performance occurs at the system level, embedding develops through practices and structures, governance operates across organizational interfaces, and survivability appears as capability continuity over time. Their alignment, rather than any single level, is the phenomenon to be explained.

8.1 Positioning the Framework within Organization and Information Systems Research

This framework bridges two major bodies of work: information systems research on AI capabilities and implementation, and organization theory on institutions, routines, learning, and resilience. Its distinctive contribution lies in the space between them: explaining how a technically sound AI system can remain organizationally meaningful, accountable, and adaptable long after initial deployment.

The explanation depends on four interlocking elements. Organizational AI Survivability defines the outcome. Organizational internalization describes how a capability is formed. Enabling governance identifies the conditions that sustain it. Cumulative governance realignment accounts for how alignment is repeatedly repaired when disruption occurs. Each element addresses a question the others cannot answer. Together, they produce a process account that existing theories, taken individually, do not provide.

8.2 Why the Framework Is More Than a Reinterpretation of Existing Theories

The framework is not a relabeling of routines, dynamic capabilities, institutionalization, or sociomaterial enactment. Each parent tradition explains a component of the phenomenon, but none independently generates the complete disruption–response sequence that the present theory specifies. More importantly, each tradition—taken alone—generates different and, in key respects, incompatible predictions about AI survivability.

Four contrasting predictions make the divergence concrete. Institutional theory treats symbolic adoption and decoupling as relatively stable equilibrium states; once decoupled, a capability can remain ceremonially intact without requiring active repair. The present framework predicts the opposite: decoupling triggers realignment episodes, and failure to realign produces progressive organizational fragility rather than stable ceremonial persistence. Dynamic capabilities theory predicts that resource reconfiguration sustains capability continuity. The framework predicts that reconfiguration may coexist with—or even accelerate—the decline of a focal AI-supported capability when enabling governance is absent. Routine dynamics predicts that endogenous variation in action patterns sustains adaptation. The framework predicts that routine persistence can conceal the erosion of accountability and interpretation, and that cross-routine responsibility requires explicit governance rather than emergent adjustment alone. Sociomaterial perspectives predict that use itself constitutes alignment. The framework predicts that use is necessary but insufficient: alignment must be deliberately regenerated across discontinuities through successive governance episodes.

These contrasting predictions are empirically distinguishable. Evidence that symbolic decoupling remains stable without governance intervention, that resource reconfiguration automatically preserves AI capability continuity, or that routine variation alone sustains accountable alignment would falsify the framework (Section 11.1). Conversely, evidence that accountable alignment depends on the proposed sequence—layered embedding, enabling governance, disruption, cumulative realignment, and renewed continuity—would support its distinct explanatory value.

The framework's distinct contribution, then, is a generative and testable counter-claim: AI survivability depends on cumulative governance realignment under disruption—not on technical metrics, symbolic legitimacy, resource reconfiguration, or situated use alone.

9. Practical and Policy Implications

For managers, the model functions as a post-implementation diagnostic. The relevant test is whether responsible use can continue when personnel, data, regulation, or strategy changes—not merely whether the system is deployed. Table 7 links each construct to evidence sources, warning signs, and governance responses.

The diagnostic should be repeated after material disruption rather than completed once at deployment. Evidence should be drawn from decision logs, exception records, escalation histories, model-monitoring reports, role descriptions, training records, and interviews with technical, operational, risk, and managerial actors. Divergence across these sources is itself evidence of weak internalization.

For boards, policymakers, and regulators, the framework implies that technical validation and formal accountability are necessary but incomplete. Oversight should examine whether responsibility survives organizational change, whether feedback leads to revised practice, and whether institutions retain the competence to interpret and challenge AI-supported decisions. Article 72 of the EU Artificial Intelligence Act requires systematic post-market monitoring of high-risk systems throughout their lifetime (European Union, 2024), while ISO/IEC 42001 requires the maintenance and continual improvement of an organizational AI management system (International Organization for Standardization, 2023). The present framework complements these requirements by explaining the organizational processes through which monitoring evidence is translated into renewed routines, decision rights, accountability, and learning after implementation.

Table 6. Organizational AI Survivability Diagnostic Checklist

Diagnostic domain	Diagnostic question	Evidence source	Warning sign	Enabling governance response
Operational embedding	Are AI outputs recorded in recurring decisions and workflows?	Workflow maps; decision logs; override and exception records	AI remains confined to dashboards, pilots, or specialist teams	Redesign workflows; define use and override points; review exceptions
Structural embedding	Are decision rights, escalation routes, and responsibility explicit?	Governance charters; role descriptions; escalation and appeal records	Responsibility shifts between technical, operational, and risk functions	Assign accountable owners; document escalation and appeal pathways
Cognitive embedding	Can managers explain the relevance, limits, and appropriate	Actor interviews; training records; interpretation	Routine acceptance, routine rejection, or dependence	Use role-based training, interpretation

	challenge of AI outputs?	and challenge reviews	on a few translators	reviews, and knowledge transfer
Cumulative governance realignment	Do incidents, drift, and contextual change produce revised rules, roles, or system design?	Incident reports; review minutes; change logs; follow-up decisions	Feedback is recorded but does not alter practice	Create closed-loop reviews with tracked decisions, owners, and dates
AI survivabilit y	After disruption, does the capability remain meaningful, accountable, and adaptable?	Usage trends; accountability records; post-disruption reviews; retirement decisions	Technical availability continues while reliance, trust, or accountability declines	Review whether to renew, redesign, restrict, or retire the capability

10. Future Research Agenda

This paper develops a conceptual process theory of Organizational AI Survivability and therefore does not empirically test its five propositions. Instead, it specifies testable constructs, observable mechanisms, competing explanations, and suitable research designs through which future qualitative, quantitative, configurational, and longitudinal studies can refine, extend, or challenge the framework.

Future studies should treat the five propositions as a coherent temporal sequence. Proposition 1 lends itself to comparative case studies or survey-based research examining the depth of operational, structural, and cognitive embedding. Proposition 2 can be tested through configurational analysis or multilevel modeling to assess whether the four functions of enabling governance operate jointly. Propositions 3 and 4 call for longitudinal and process-oriented designs that track disruption episodes, governance responses, changes in alignment, and subsequent capability continuity. Proposition 5 can be examined through matched comparisons, event-history analysis, or survival models to determine whether restrictive-only governance increases the risk of progressive decoupling and capability retirement.

Agentic AI represents a particularly important context for extending the framework. Greater autonomy may compress the window available for human interpretation and governance response. Future research should investigate whether agentic systems increase the frequency or intensity of the realignment episodes required and whether enabling governance moderates the relationship between autonomy and capability fragility. Such studies should also explore whether the framework's proposed governance functions remain sufficient when AI systems can initiate actions with limited human oversight.

Appendix A offers illustrative dimensions and sample items as a foundation for measurement development. These should be refined through qualitative elicitation, expert review, item purification, and rigorous validation. Longitudinal designs will benefit from multiple waves of data collection anchored around meaningful disruption events. Depending on the research question, suitable methods may include structural equation modeling, latent growth modeling, process tracing, event-history analysis, or fuzzy-set qualitative comparative analysis (fsQCA).

Ultimately, empirical research can refine, extend, or challenge the framework rather than simply confirm it. Findings that identify boundary conditions, substitute mechanisms, or contexts in which technical performance persists without the proposed forms of internalization and governance will be especially valuable. Such work will clarify not only why organizations sometimes fail before AI fails, but also the precise limits of this process theory.

Table 7. Future Research Directions for Empirical Examination of the Framework

Proposition	Unit and sampling logic	Evidence and time design	Suitable analysis and principal test
P1: Joint layered embedding → internalization	AI initiatives nested within organizations; purposive variation in embedding depth, followed by multisector sampling	Workflow records, role structures, surveys, interviews; cross-sectional validation followed by repeated measures	CFA/SEM or comparative case analysis; test whether joint operational, structural, and cognitive embedding explains internalization beyond deployment intensity
P2: Four enabling-governance functions → internalization	Organizations with contrasting restrictive and enabling governance configurations	Governance documents, decision logs, actor surveys and interviews; pre/post governance change where possible	Multilevel SEM, configurational analysis, or difference-in-differences; test the distinct and joint roles of routine alignment, accountability allocation, interpretive coordination, and learning integration
P3: Disruption-triggered realignment → survivability	AI capabilities observed through multiple disruption and response episodes	Event histories, governance reviews, incident logs, decision records, and interviews across multiple disruption–response episodes	Process tracing, sequence analysis, or temporal bracketing; test whether governance episodes restore accountable alignment before capability continuity improves
P4: Cross-episode accumulation	Organizations undergoing leadership, regulatory, structural, or workforce change	Measures before disruption, after governance response, and after stabilization	Event-history, longitudinal case comparison, or latent-growth analysis; test whether retained changes from prior episodes

→ continuity of internalization			improve preservation or recovery of embedding after later disruption
P5: Restrictive-only governance → progressive decoupling	Matched AI initiatives with comparable technical maturity but different governance orientation	Technical metrics plus reliance, accountability, exception, and learning evidence across disruption	Matched comparison, survival analysis, or fsQCA; test whether failure to revise routines, responsibilities, interpretation, and learning increases decoupling and retirement risk

11. Boundary Conditions

The explanation assumes a minimum substrate of digital infrastructure, governance capacity, and managerial engagement. Where AI remains an isolated experiment or is disconnected from recurrent work, there is too little organizational embedding for the proposed realignment mechanism to operate.

Organizational size may also alter the framework's operation. Smaller organizations may coordinate AI use rapidly because they have fewer structural layers, yet this apparent flexibility can conceal dependence on a small number of technical or managerial actors. When knowledge, decision authority, and interpretive competence are concentrated in a few individuals, turnover can simultaneously weaken operational, structural, and cognitive embedding. In such settings, survivability may depend less on formal governance complexity than on role redundancy, knowledge transfer, and continuity of responsibility.

Second, the framework recognizes that organizational conditions influence the effectiveness of enabling governance. Factors such as regulatory discontinuity, political instability, workforce turnover, strategic uncertainty, persistent data-quality challenges, and limited managerial commitment may restrict the ability of governance mechanisms to maintain alignment around AI.

These conditions make the theory contingent rather than universal. Enabling governance can strengthen internalization, but it cannot guarantee continuity when actors lack authority, usable evidence, or the capacity to learn from disruption.

Explanatory power should decline in settings with extremely low digital maturity, fragmented decision authority, severe resource constraints, or no basic governance arrangements. Here, failure may arise before internalization begins, making capability formation—not post-implementation realignment—the prior theoretical problem.

Empirical tests should therefore compare organizations that differ in digital maturity, resource concentration, regulatory exposure, and continuity of decision authority. Such variation can reveal when governance realignment operates and when its preconditions are absent.

11.1 Conditions for Theoretical Falsification

To establish boundaries for falsification, this process theory would be challenged or rendered non-explanatory under three specific empirical conditions. First, if longitudinal evidence demonstrates that an organization maintains long-term capability continuity and adaptive alignment following major disruptions solely through technical availability and automated re-training—without active operational, structural, or cognitive embedding—the core proposition (P_1) would be falsified. Second, if restrictive, compliance-only governance configurations consistently achieve high levels of capability adaptability and interpretive retention across organizational shocks without activating enabling alignment functions, P_5 would not hold. Third, if repeated governance realignment episodes fail to leave observable traces in routines, decision rights, or institutional memory (P_4), yet capability survivability persists at the same rate as in high-alignment settings, the proposed cumulative process mechanism would be empirically redundant. Specifying these boundaries ensures that Organizational AI Survivability functions as a testable, falsifiable process framework rather than an all-encompassing tautology.

12. Conclusion

Successful deployment does not establish AI survivability. Organizations can operate a technically competent system while the routines, decision rights, interpretive competence, and learning processes that make it useful are already weakening.

The proposed theory explains that divergence through four linked concepts: digital implementation without organizational internalization, layered internalization, enabling governance, and cumulative governance realignment. An AI-supported capability endures when accountable alignment is reproduced across successive disruptions; it becomes fragile when technical operation outlives the organizational relationships that give it consequence.

Zillow Offers does not test the theory, but it shows what the theory directs an investigator to examine: how prediction interacted with operating routines, decision rights, inventory commitments, feedback, and governance capacity. The diagnostic lesson is deliberately narrower than a causal claim: technical performance alone cannot explain AI failure when organizational exposure is produced through these interdependent organizational conditions.

Organizations may therefore fail before AI fails.

Declaration of Generative AI and AI-Assisted Technologies

During preparation of this manuscript, generative AI tools were used for language refinement, grammatical correction, readability enhancement, non-substantive document formatting, and figure-label consistency. All theoretical constructs, conceptual distinctions, proposed mechanisms, and scholarly judgments remain the author's responsibility. No AI-generated output was accepted without author review and verification. The author assumes full responsibility for the accuracy, originality, and integrity of the manuscript.

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Appendix A. Illustrative Measurement Dimensions for Future Empirical Research

The framework developed in this study is conceptual and is not intended to provide a validated measurement instrument. However, future empirical research may operationalize the proposed constructs through the illustrative dimensions presented below.

Construct	Illustrative Dimensions
Organizational Internalization	Operational Embedding
Organizational Internalization	Structural Embedding
Organizational Internalization	Cognitive Embedding
Enabling Governance	Routine Alignment
Enabling Governance	Accountability Allocation
Enabling Governance	Interpretive Coordination
Enabling Governance	Learning Integration
Cumulative Governance Realignment	Restoration of Accountable Alignment
Cumulative Governance Realignment	Governance Response Accumulation
Cumulative Governance Realignment	Cross-Episode Learning
AI Survivability	Durability of Use

AI Survivability	Accountability Continuity
AI Survivability	Learning Continuity
AI Survivability	Sustained Value Creation

These dimensions are illustrative rather than definitive. Their purpose is to support future scale development, longitudinal investigation, and empirical testing of the relationships proposed in the framework.

Illustrative Sample Measurement Items

Construct	Sample Item
Organizational Internalization	AI outputs are routinely used in daily operational workflows.
Organizational Internalization	Managers rely on AI-supported evidence during decision-making.
Enabling Governance	AI outputs are explicitly connected to recurrent operating routines and escalation paths.
Enabling Governance	Decision rights for accepting, overriding, and revising AI-supported recommendations are clearly allocated.
Enabling Governance	Technical and operational actors regularly develop shared interpretations of AI outputs and limitations.
Enabling Governance	Errors, exceptions, overrides, and contextual changes lead to revisions in both AI systems and organizational practice.
Cumulative Governance Realignment	Governance processes help reconnect AI outputs to organizational objectives after disruption.
Cumulative Governance Realignment	Feedback loops are reactivated when organizational conditions change.
AI Survivability	AI-supported capabilities remain actively used during organizational change.
AI Survivability	AI-supported decisions remain trusted after leadership or structural transitions.

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