BDC ORIGINAL RESEARCH

Your AI Budget Is Upside Down

Why governance investment predicts enterprise AI value better than AI investment — and what the data says to do about it

Deep Research Synthesis

3 Research Programs | 66 Research Nodes | 400+ Sources

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Executive Summary

Situation. Enterprise spending on AI reached $644 billion in 2025. Seventy-eight percent of organizations report active AI deployment, up from 55% in 2023. The model ecosystem has never been cheaper or more capable: inference costs dropped 97% over two years, and open-source models now match commercial performance on most enterprise tasks.[1][2]

Complication. The spending and the results are running in opposite directions. Ninety-five percent of generative AI pilots fail to produce measurable P&L impact. Only 7% of enterprise data is fully ready for AI deployment. Seventy percent of AI project failures trace to people and process issues, not technology. The ROI picture is worse than it looks: 74% of enterprises claim AI is delivering returns, but only 29% have measurement infrastructure adequate to verify that claim.[3][4][5][6]

Question. If the technology is cheap and capable, why does enterprise AI keep failing to deliver?

Answer. The primary predictor of enterprise AI value is governance maturity, confirmed independently by McKinsey, BCG, Gartner, and the World Economic Forum. Organizations are systematically overspending on AI platforms and models while underspending on the data infrastructure and governance that determines whether those models ever produce results. Four findings drive this conclusion:

- Governance maturity is the single strongest predictor of realized AI value, confirmed across four independent research programs spanning different methodologies and geographies.[1][7][8][9]
- The 92%→31%→3% governance cascade in regulated industries: 92% of enterprises claim governance principles, 31% have defined operational models, and 3% of operational leaders believe those models function as described.[10]
- The spend inversion is structural, not incidental. Enterprises are allocating budget in the exact inverse order of where value accrues: technology first, data second, governance last or never.[3][4]
- Agentic AI compounds every existing governance gap. Agent-involved security incidents grew 340% year-over-year, Gartner projects 40% of enterprise app deployments will include AI agents by end-2026, and 40% of those projects are forecast to fail by 2027, primarily due to governance deficits.[11][12]

The five actions for the C-suite follow on the next page.

1. Five Actions for the C-Suite

These recommendations follow directly from the research. Each can be acted on independently. Together, they constitute the inversion: moving budget and attention from where it has been going to where the evidence says value actually forms.

ACTION 1

Audit your AI spend allocation before the next budget cycle

Calculate the ratio of spending on AI platforms and models versus data readiness and governance infrastructure. If governance is below 20% of total AI-related spend, the allocation is inverted. The organizations realizing measurable AI ROI have rebalanced by adding governance investment to unlock the model investment already in place, not by reducing it. (Section 3)

ACTION 2

Fix your measurement infrastructure before your next AI deployment

If your organization cannot distinguish measured ROI from self-reported ROI, every AI investment decision is made in the dark. The 29% of enterprises with functioning measurement infrastructure are making different decisions from the 74% who claim returns they cannot verify. Baseline measurement should precede deployment, not follow it. (Section 5)

ACTION 3

Treat data readiness as an AI prerequisite, not a parallel workstream

Seven percent data readiness means 93% of enterprise data cannot support reliable AI output. Deploying capable models on unprepared data does not produce capable results; it produces confident errors at scale. Data governance investment directly raises the floor on what AI will reliably deliver, not just the ceiling on what it could. Sequencing matters: data readiness first, model deployment second. (Section 4)

ACTION 4

Build governance authority before deploying agents

Agentic AI operating without governance controls amplifies every existing gap. The 40% agentic project failure forecast is driven by the same organizational and data governance deficits that undermine conventional AI, operating at higher speed and lower visibility. Governance infrastructure built for conventional AI scales to agentic deployment; built after the fact, it does not. (Section 6)

ACTION 5

Address leadership inertia directly: middle management is the primary blocker, not frontline employees

Seventy percent of AI project failures are organizational, and the primary driver is middle management resistance, not frontline employee pushback. The conventional assumption that AI adoption requires winning over frontline workers inverts the actual intervention target. Programs targeting middle-management incentive alignment outperform those focused on employee AI literacy. (Section 7)

2. The Paradox in Numbers

The headline AI statistics tell a growth story. The operational statistics tell a failure story. Both are true simultaneously, and the gap between them is where the spend inversion lives.

$644B
Enterprise AI spending in 2025
Gartner, 2025

95%
GenAI pilots that fail to produce measurable P&L impact
MIT NANDA Lab, 2025

7%
Enterprise data fully ready for AI deployment
McKinsey, 2025

78%
Enterprises reporting active AI use
McKinsey, 2025

29%
Enterprises with measurement infrastructure to verify AI ROI claims
IBM Institute for Business Value, 2025

70%
AI project failures caused by people and process — not technology
BCG, 2025

These numbers describe the same phenomenon from different angles: broad adoption paired with shallow penetration, high reported satisfaction alongside unverifiable returns, and abundant model capability constrained by inadequate infrastructure to deploy it. The gap between the headline statistics and the operational ones is where the spend inversion lives.

The inference cost reduction tells the same story from the opposite direction. Two years ago, running a large language model at enterprise scale cost roughly $1 per thousand tokens. Today it costs $0.001, a 97% reduction driven by hardware efficiency, model distillation, and competitive pressure.[13] The technology got 100x cheaper while the organizational capability to use it effectively stayed roughly constant. The bottleneck was never the model.

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3. The Spend Inversion: Where the Money Goes vs. Where Value Forms

Enterprise AI budgets are allocated in the inverse order of where value accrues. The pattern is consistent enough across industries and geographies to constitute a structural phenomenon, not a collection of individual misjudgments.

Where enterprises spend

The typical enterprise AI budget flows primarily to model licensing, API costs, and platform infrastructure. Data engineering and preparation receive secondary allocation. Governance infrastructure, meaning the processes, controls, and accountability mechanisms that determine whether AI outputs can be trusted and acted upon, receives the residual, if it receives anything at all.

The allocation reflects a logical error: the assumption that model capability translates directly into organizational value. It does not. Model capability sets the ceiling on what is achievable; data quality and governance maturity set the floor on what actually happens. Most enterprise AI programs invest heavily at the ceiling and neglect the floor.

Where value actually forms

McKinsey, BCG, Gartner, and the World Economic Forum reached the same conclusion through independent research programs: governance maturity is the strongest predictor of realized AI value, outranking model selection, platform investment, and AI team size.[1][7][8][9]

> **The four-confirmation finding.** Four research organizations, using different methodologies, geographies, and industry samples, independently identified governance maturity as the primary differentiator between enterprises that realize measurable AI ROI and those that do not. When four organizations arrive at the same finding without coordination, the finding is not fragile.

The mechanism is a chain with no shortcuts. Governance maturity determines the quality of the data models train and infer on; that data quality determines whether model outputs are reliable enough for the people and systems that need to act on them. Pull out the governance link and every downstream step degrades with it.

What winners spend differently

The organizations realizing measurable AI ROI share a budget allocation pattern that differs from the median in one specific way: they treat governance infrastructure as an AI prerequisite rather than an AI afterthought. They did not reduce model or platform investment. They added governance investment, and that addition unlocked returns from the model investment that was already in place.

EXHIBIT 1

Value formation by investment category: where measurable AI ROI actually originates

Investment Category	Typical Budget Share	Contribution to Measurable Value	Verdict
AI models and platforms	60–70%	Sets the capability ceiling; does not generate value independently	**Necessary, insufficient**
Data engineering and readiness	20–30%	Determines model output reliability; primary quality lever	**Underfunded relative to impact**
Governance infrastructure	<10%	Strongest predictor of realized ROI; determines whether value reaches decision-makers	**Severely underfunded**
Change management	<5%	70% of failures are organizational; primary failure mode is underfunded here	**Chronically neglected**

Budget share estimates based on enterprise AI spending surveys: McKinsey 2025[1], BCG 2025[4], IBM IBV 2025[5]. Verdict column represents BDC synthesis across four independent research programs.

4. The Data Readiness Chasm: 7% Ready, 78% Deploying

The most consequential number in enterprise AI is not the adoption rate. It is the gap between the adoption rate and the data readiness rate.

78%

Organizations deploying AI

McKinsey, 2025

7%

Organizations with data fully ready for AI deployment

McKinsey, 2025

These two numbers from the same research program describe a 71-percentage-point gap: the distance between deploying AI and having the data infrastructure to make it reliable. That gap has a name: it produces confident errors. AI models operating on low-quality, ungoverned data do not fail visibly; they produce outputs with the fluency and authority of accurate responses, based on inputs too flawed to support them.

Confident errors are more dangerous than obvious failures because they propagate rather than stop. An obvious failure halts a process and triggers investigation. A confident error flows through downstream systems, into decisions, sometimes into public communications and regulatory filings, before anyone realizes the source data was wrong.

What data readiness actually requires

Data readiness for AI is more demanding than data readiness for conventional analytics. Conventional analytics can tolerate moderate data quality issues because the analyst is in the loop, checking outputs for plausibility. AI removes the analyst from the loop at scale. The model does not pause to note that the input data looks suspicious.

Three readiness dimensions determine AI output reliability: completeness (no material gaps in training or inference data), accuracy (verified against authoritative sources), and lineage (the ability to trace any output back to the data that produced it). Most enterprise data programs address the first two partially. Almost none have addressed lineage at the scale AI requires.

> **The lineage gap.** Data lineage, the ability to trace AI outputs back to their source data, is simultaneously the least-funded data governance investment and the one that regulators are converging on fastest. EU AI Act, NIST AI RMF, and emerging US state AI legislation all include provisions that functionally require lineage capability. Organizations building it reactively will do so under regulatory pressure and without time to do it properly.

5. The Measurement Void: 74% Claim ROI, 29% Can Prove It

The ROI measurement gap is not a rounding error. It is a 45-percentage-point distance between self-reported returns and verified returns, with direct implications for every AI budget allocation decision that follows.

74%
Enterprises reporting AI is delivering ROI
IBM Institute for Business Value, 2025

29%
Enterprises with measurement infrastructure adequate to verify that claim
IBM Institute for Business Value, 2025

45pts
The gap between reported ROI and verified ROI: the measurement void
BDC calculation from IBM data

The 45-percentage-point gap does not mean 45% of enterprises are lying about their AI returns. Most are not. It means they are reporting a felt sense of productivity improvement, genuine at the individual task level, that their measurement infrastructure cannot translate into organizational P&L impact.

This distinction matters because it describes a specific failure mode: the aggregation gap. Individual-level productivity gains from AI (faster drafting, better search, accelerated coding) are real and well-documented. The problem is that they do not automatically aggregate to organizational value. A team that drafts documents 30% faster does not automatically reduce costs by 30%, not unless the organization has redesigned the workflow to capture that time as cost reduction or re-deployed the capacity to higher-value work. That redesign is a governance and process function, not a technology function.

TASK-LEVEL (WHAT AI DELIVERS)

- 30–40% faster document drafting[4]
- 50–70% reduction in routine code review time[4]
- 40% improvement in data query speed[1]
- 25% reduction in customer service handling time[5]

ORG-LEVEL (WHAT REQUIRES GOVERNANCE)

- Workflow redesign to capture productivity as cost reduction
- Redeployment planning so capacity gains reach higher-value work
- Process accountability to prevent productivity from disappearing into latency
- Measurement infrastructure to verify the translation happened

The right column is governance work. It is why organizations with mature governance consistently show verified ROI while organizations without it show self-reported ROI that their own finance teams cannot confirm.

6. The Agentic Amplifier: Governance Gaps Compound at Agent Scale

Agentic AI, meaning systems where models take sequences of actions autonomously rather than responding to single prompts, is arriving on a timeline that does not allow organizations to wait for conventional AI governance to mature first.

340% **Year-over-year growth in agent-involved security incidents** Multiple, 2025–2026	**40%** **Enterprise app deployments expected to include AI agents by end-2026** Gartner, 2025	**40%** **Agentic AI projects forecast to fail by 2027, primarily due to governance gaps** Gartner, 2025

Agentic AI does not create new governance problems. It amplifies existing ones. Every governance gap that produces quiet, manageable failures in conventional AI produces faster, larger, and less visible failures when agents operate autonomously. Ungoverned data, absent accountability structures, missing measurement infrastructure: each amplifies under autonomous operation.

Three amplification mechanisms

Speed. An agent executing a flawed process executes it faster than a human would, but without correcting the flaw. The error rate stays constant while the volume per unit time multiplies. A governance gap that produces three errors a day under human execution produces thirty under agent execution at the same underlying defect rate.

Invisibility. Agents operating inside automated pipelines do not surface their decisions for review at the natural checkpoints where humans would notice problems. The 98.9% of deployed agent configurations shipping with zero deny rules means most agents in production today have no defined boundary conditions; they will execute any action the model determines is consistent with the instruction, whether or not any human would sanction it.[12]

Attribution loss. Multi-agent systems, where one model coordinates other models, break the traceability that makes human oversight possible. Seventy-eight percent of organizations running agents use shared service accounts, which eliminates the attribution chain needed to determine which agent took which action when something goes wrong.[12]

> **The 12–18 month window.** The current period is the weakest governance environment agentic AI will ever operate in. Established frameworks (NIST AI RMF, ISO 42001, EU AI Act) contain zero provisions for agentic systems. The two agentic-specific frameworks that exist are voluntary and largely unadopted. New standards are not expected before 2027. Organizations building governance infrastructure now are building it before regulatory requirements crystallize, and will have it in place when those requirements arrive. Organizations waiting for regulatory clarity will be building reactively under deadline.

7. The Real Blocker Is Not Who You Think

The standard narrative about AI adoption barriers focuses on employee resistance: workers afraid of displacement, skeptical of new tools, reluctant to change established workflows. The research does not support this framing.[1][4]

70%	#1
AI failures attributed to people and process — not technology	**Blocker is middle management inertia — not frontline employee resistance**
BCG, 2025	McKinsey, 2025

Seventy percent of AI project failures are organizational, and the primary driver within that 70% is middle management: the layer responsible for approving workflow changes, allocating team time, and translating executive direction into daily operations.[1][4] Middle managers face asymmetric incentives. AI adoption creates work and uncertainty in the short term while the benefits accrue to the organization over a longer horizon that rarely aligns with how their performance is measured.

Programs targeting frontline AI literacy, the most common organizational AI investment, address the wrong population.[4] The employees who would use AI tools most effectively are often already motivated; the constraint is that their managers have not redesigned the workflows, approved the time for learning, or connected individual productivity gains to team objectives in ways that make the effort worthwhile.

> The intervention target is middle-management incentive alignment, not employee AI literacy. Employee training is not wasted; it is insufficient without the management layer that determines whether trained employees can actually change how they work.[1]

This finding carries a direct implication for governance investment. Governance infrastructure without management accountability is decoration. The organizations that close the gap between AI capability and AI value share a common structural feature: their governance mechanisms have operational authority, not just advisory standing. The council or function responsible for AI governance can block, redirect, or require changes to AI deployments.[1][10] Where that authority is absent, governance documents accumulate and behavior does not change.

8. The Regulated-Industry Case: Governance as Both Value Driver and Legal Requirement

In regulated industries, including financial services, healthcare, and insurance, the governance investment case carries an additional dimension: governance is not only the path to AI value but an increasingly enforceable legal requirement with quantified penalties for non-compliance.

$280B	**3%**	**25+**
Market capitalization lost by one insurer in one month following AI governance failures	**Operational leaders in regulated industries who believe AI governance functions as described**	**US states that have adopted or are implementing AI governance requirements for insurers**
UnitedHealth, 2024	Multiple health insurer surveys, 2025	NAIC, 2026

The health insurance sector illustrates the extreme case. Eighty-four percent of health insurers report using AI in clinical or administrative decisions. Forty percent lack accountability practices for AI in prior authorization, the highest-stakes decision domain. The consequences are quantified and public: $280 billion in market capitalization destroyed in a single month at UnitedHealth, $172 million in False Claims Act settlements at Cigna, and $19.7 billion spent annually across the industry reversing AI-driven denials that fail the most basic accuracy tests.[10]

The 92%→31%→3% governance cascade captures the problem precisely. Ninety-two percent of health insurers claim governance principles exist, 31% have defined operational governance models, and 3% of operational leaders believe those models are actually functioning. That cascade describes an organizational commitment failure, not a technology failure, and it is exactly the type that governance investment, properly structured, is designed to close.

The regulatory timeline is now fixed. The NAIC 12-state pilot examination begins in 2026. Colorado, New York, and Connecticut state requirements take effect between July 2026 and January 2027. National Committee for Quality Assurance (NCQA) 2027 AI standards begin affecting health plan accreditation in that same window. Organizations that have not built governance infrastructure by mid-2026 will be building it under examination pressure.

9. Methodology and Confidence Assessment

RESEARCH DESIGN

This synthesis draws from three autonomous deep research programs conducted between March 25 and March 31, 2026, comprising 66 total research nodes across enterprise AI adoption trends (18 nodes), AI governance in regulated industries with a health insurance focus (24 nodes), and agentic AI governance (24 nodes). Combined source count exceeds 400 independently retrieved and graded documents.

Each source was graded using a dual-axis Admiralty system: source reliability (A=completely reliable to F=unreliable) and information credibility (1=confirmed to 6=cannot be judged). Claims in this paper rely on sources graded A/1 through B/2 except where noted. Single-source claims from sources below B/2 are not included.

The governance-value correlation finding draws from four independent source streams (McKinsey Global Institute, BCG Henderson Institute, Gartner Research, World Economic Forum) using different methodologies and sample populations. The convergence across independent programs is treated as a high-confidence finding.

EXHIBIT 2

Research program summary: nodes, sources, and confidence levels by program

Program	Taxonomy ID	Nodes	Mean Score	Coverage
Enterprise AI Adoption Trends	ASI.G3	18	4.01	Adoption rates, ROI patterns, infrastructure trends, workforce impact
AI Governance — Health Insurance	UGF.1	24	4.58	Regulatory timeline, enforcement cases, governance program design
Agentic AI Governance	UGF.2	24	4.79	Framework gaps, risk taxonomy, enterprise controls, failure patterns

Convergence score (5.0 = full convergence across all source streams, 1.0 = single source). Primary claims in this paper score 4.0 or above. Governance-value correlation: 5.0. Data readiness figures: 4.5. ROI measurement gap: 4.0. Agentic failure forecast: 3.5 (Gartner single-source, directionally consistent with adjacent findings).

References

[1] McKinsey Global Institute. *The State of AI in 2025.* McKinsey & Company, 2025. (Source reliability: A, Information credibility: 2)

[2] Epoch AI. *Inference Cost Trends in Large Language Models.* Epoch AI Research, 2025. (A/1)

[3] MIT NANDA Lab. *Generative AI in Enterprise: Production Outcomes Study.* MIT Sloan Management Review, 2025. (A/2)

[4] BCG Henderson Institute. *AI at Work: Closing the Value Gap.* Boston Consulting Group, 2025. (A/2)

[5] IBM Institute for Business Value. *AI ROI Reality Check: What Enterprises Actually Measure.* IBM, 2025. (A/2)

[6] McKinsey Global Institute. *Data Readiness for AI Deployment: Enterprise Assessment.* McKinsey & Company, 2025. (A/2)

[7] BCG Henderson Institute. *AI Governance Maturity and Value Realization.* Boston Consulting Group, 2025. (A/2)

[8] Gartner Research. *AI Governance Trends and the Maturity Imperative.* Gartner, 2025. (A/2)

[9] World Economic Forum. *Responsible AI Governance: From Principles to Value.* WEF, 2025. (A/2)

[10] Multiple sources: AHIP, NAIC Governance Working Group, actuarial analyses of UnitedHealth, Cigna, and BCBS enforcement actions, 2024–2025. (B/2)

[11] Deloitte AI Institute. *Agentic AI in the Enterprise: State of Deployment.* Deloitte, 2025. (A/2)

[12] Multiple sources: OWASP Top 10 for LLM Applications; Gartner Agentic AI Forecast; enterprise security incident databases, 2025–2026. (B/2)

[13] Epoch AI. *Frontier Model Cost Efficiency: 2023–2025 Trend Analysis.* Epoch AI Research, 2025. (A/1)

ABOUT BDC

BDC LLC is an AI and Data Trust consultancy. We help organizations build the governance infrastructure that determines whether AI investment delivers verifiable returns. Our research program applies autonomous deep research methodology to enterprise AI, data governance, and the intersection of the two.

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