

The Business Value of AI: Decision Productivity, Coordination Costs, and the Governance of Intelligent Systems

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Abstract

Despite unprecedented investment in artificial intelligence (AI), empirical evidence of systematic firm-level productivity gains remains uneven. This pattern mirrors the historical “IT productivity paradox,” in which information technology spending failed to correlate consistently with profitability. Building on the managerial productivity thesis articulated in *The Business Value of Computers* by Paul A. Strassmann (1990), this paper develops a formal theoretical framework explaining AI value creation as a function of decision productivity relative to coordination and governance costs.

We define decision productivity as the multiplicative interaction of decision impact (Q), decision velocity (S), and decision scale (L). AI generates economic value when improvements in these dimensions outpace the organizational burdens introduced by coordination complexity (CC₁) and governance overhead (GC₂). The resulting model predicts four AI value regimes: cosmetic AI, bureaucratic AI, value destruction, and structural advantage.

The framework contributes to strategy and information systems research by: (i) reframing AI as an organizational architecture intervention rather than a technological artifact; (ii) introducing coordination and governance costs as moderating variables in AI performance outcomes; and (iii) offering testable hypotheses linking decision redesign to firm-level economic impact. Implications for corporate governance and AI oversight are discussed.

Keywords: *artificial intelligence, decision productivity, coordination costs, governance, IT productivity paradox, organizational architecture, competitive advantage*

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1. Introduction

Artificial intelligence (AI) is widely described as a general-purpose technology that can reshape productivity, competition, and organizational design. Firms across industries are investing heavily in generative AI, predictive analytics, and autonomous systems. However, despite rapid advances in model capability, evidence of systematic and sustained firm-level performance improvement remains heterogeneous. Some organizations report material margin expansion and decision-cycle compression; others experience cost escalation, governance complexity, and negligible financial return.

This divergence parallels the historical information technology (IT) productivity paradox. During the expansion of enterprise computing in the late twentieth century, firms dramatically increased IT expenditure without consistent improvement in profitability (Brynjolfsson, 1993; Solow, 1987). In a landmark response to this apparent paradox, Strassmann (1990) argued in *The Business Value of Computers* that IT does not directly generate business value. Rather, IT enhances profitability only when it improves management productivity. Technology acts as a multiplier of organizational effectiveness rather than a self-sufficient source of economic return.

The present AI environment exhibits analogous structural characteristics. While AI capabilities have advanced at unprecedented speed, economic outcomes differ sharply across firms. This paper proposes that the key explanatory variable is not technological sophistication *per se*, but the organizational architecture within which AI is deployed.

We introduce the AI Value Framework (AIVF), which conceptualizes AI value creation as a function of decision productivity relative to the costs of coordination and governance. AI affects organizations primarily by altering how decisions are generated, evaluated, and executed. When AI improves decision impact, accelerates decision velocity, and expands decision scale—without proportionally increasing coordination and governance burdens—it creates durable economic value. Conversely, when AI increases organizational complexity faster than it improves decision productivity, net value declines or is eliminated.

This framework contributes to strategy, information systems, and corporate governance research by formalizing AI as an intervention in decision systems and by specifying the structural conditions under which AI investment produces competitive advantage. The paper proceeds as follows. Section 2 develops the theoretical foundations. Section 3 presents the formal model. Section 4 operationalizes the constructs. Section 5 derives the value quadrant. Section 6 presents the AI maturity ladder. Sections 7 through 9 develop implications for empirical research, strategy, and governance. Section 10 concludes

2. Theoretical Foundations

2.1 AI as a General-Purpose Technology

General-purpose technologies (GPTs) reshape economic systems by enabling complementary innovations and altering organizational structures (Bresnahan & Trajtenberg, 1995; Lipsey, Carlaw, and Bekar, 2005). GPTs are characterized by pervasiveness, continuous

improvement, and the spawning of complementary innovations. AI exhibits precisely these characteristics: it is broadly applicable across industries and functions, continuously improving through advances in model architecture and training, and generating combinatorial value when integrated with other digital systems (Agrawal, Gans, and Goldfarb, 2018; Cockburn, Henderson, and Stern, 2018).

However, the historical record on GPTs demonstrates that economic impact depends critically on complementary organizational change. Brynjolfsson and McAfee (2014) found that firms that paired IT investment with organizational redesign—including changes to business processes, decision rights, and talent structures—captured disproportionately large returns. Technology layered onto legacy bureaucratic systems, by contrast, often amplified inefficiencies rather than eliminating them. The same dynamic appears to be operating with AI today.

2.2 The Managerial Productivity Thesis

Strassmann's (1990) central proposition was that IT enhances profitability only when it increases management productivity. Management productivity reflects the efficiency and effectiveness with which firms coordinate resources and make decisions. Critically, Strassmann found that IT spending per se showed no consistent correlation with return on equity or profitability across a large sample of U.S. firms. The determining variable was not the level of technology investment but whether that investment was channeled into genuinely productive managerial activity.

Strassmann also introduced the concept of Return-on-Management (ROM), defined as the ratio of management value added to management costs. This ratio captures the efficiency with which organizational coordination converts inputs into strategic outcomes. Firms with high ROM—those with lean, effective decision-making structures—reaped the benefits of IT; firms with low ROM saw technology expenditures swallowed up by administrative overhead.

We extend this thesis to AI, arguing that AI's principal economic function is to modify the productivity of decision systems. The relevant analytic unit is not the AI model but the decision architecture: the system of rights, processes, information flows, and incentives through which consequential choices are made and executed. Return-on-Intelligence (ROI)—a construct we introduce below—is the AI-era analog of Strassmann's ROM.

2.3 Coordination and Governance Costs

Transaction cost economics (Coase, 1937; Williamson, 1975, 1985) emphasizes that firms exist in part to reduce the costs of market coordination. Within firms, coordination costs remain substantial: aligning information, reconciling incentives, managing approval chains, and monitoring agent behavior all consume organizational resources. Jensen and Meckling (1976) further highlight agency costs as a persistent drag on organizational efficiency.

AI adoption introduces a new and underappreciated source of friction. While AI may reduce certain operational costs—automated document drafting, accelerated data analysis, real-time anomaly detection—it simultaneously increases oversight burdens, compliance requirements, integration complexity, and the need for human-in-the-loop validation. Organizations deploying AI at scale must manage model auditability, data governance,

regulatory alignment, and the organizational politics of algorithmic authority (Dafoe, 2018; Makridakis, 2017).

The net economic value of AI, therefore, depends on the balance between productivity gains and the organizational friction introduced. This balance is the central concern of the framework developed in Section 3.

3. The AI Value Framework

3.1 Core Proposition

The AIVF rests on two core propositions.

Proposition 1 (AI Value Condition). AI generates positive firm-level economic value when increases in decision productivity exceed increases in coordination and governance costs.

Formally, we define the AI Value Index (V_{ai}) as:

$$V_{AI} = (Q \times S \times L) / (CC_1 + GC_2)$$

where Q = Decision Impact, S = Decision Velocity, L = Decision Scale

CC_1 = Coordination Cost, GC_2 = Governance Cost

Decision productivity—the numerator—is the multiplicative product of three dimensions: decision impact (Q), decision velocity (S), and decision scale (L). These are detailed in Section 4. The denominator captures organizational friction introduced or amplified by AI adoption: coordination costs (CC_1) and governance costs (GC_2). AI creates net positive value when $V_{ai} > 1$ and is improving relative to a pre-AI baseline. It destroys value when the denominator grows faster than the numerator.

Proposition 2 (Variance Amplification). AI amplifies existing managerial effectiveness. Firms with strong governance, clear decision rights, and aligned incentive structures convert AI investment into economic gain. Firms with weak organizational structures experience amplified inefficiency.

This proposition implies a distributional prediction: AI adoption should be associated with increasing variance in firm performance within industries. Firms that are well-organized before AI deployment will compound their advantage; poorly organized firms will compound their dysfunction. This pattern is consistent with early empirical evidence from the current wave of generative AI deployment, in which some firms report 30–50% productivity improvements in specific decision domains while others report negligible impact despite comparable technology expenditure (Brynjolfsson, Li, and Raymond, 2023; Dell'Acqua et al., 2023).

3.2 Return-on-Intelligence

Extending Strassmann's Return-on-Management construct, we propose Return-on-Intelligence (ROI) as the primary metric for evaluating AI's organizational contribution:

$$\text{Return-on-Intelligence} = (\text{Decision Impact} \times \text{Velocity} \times \text{Scale}) / (\text{Cognitive Cost} + \text{Governance Cost})$$

The scarce resources in the AI era are not computational—these are increasingly commoditized—but organizational: executive attention, decision bandwidth, and cognitive capacity for judgment. AI creates value when it reduces the cognitive and governance cost of high-quality decision-making, not when it merely generates more information or automates low-leverage tasks.

The distinction is consequential. Many current AI deployments target internal productivity—drafting emails, summarizing meetings, and generating slide content. These applications may reduce individual cognitive effort but do not structurally alter the decision systems that create competitive advantage. We term these “cosmetic AI” deployments: they produce the appearance of transformation without structural change. As Strassmann would observe, the constraint is not model intelligence but organizational architecture.

4. Construct Development

The AIVF comprises five empirically distinct constructs. Table 1 provides a diagnostic scoreboard for each. The core diagnostic question animating the framework is: Is AI increasing our decision productivity (impact, velocity, scale) faster than it is increasing our coordination and governance burden? If organizational leadership cannot answer this question quantitatively, AI governance is immature.

Table 1. AI Value Diagnostic Scoreboard

Dimension	Healthy Signal (Score: 5)	Red Flag (Score: 1)
Decision Impact (Q)	EBITDA-linked decision gains	No quantified decision improvement
Decision Velocity (S)	Material compression of decision cycles	AI pilots running; decision rights unchanged
Decision Scale (L)	AI deployed across revenue-generating processes	AI tools confined to internal productivity
Coordination Burden (CC ₁)	Managerial complexity simplified vs. complexity exploding	New committees, review layers, shadow governance
Governance Efficiency (GC ₂)	Governance proportional to risk, enabling scale vs. blocking value	Blanket approvals, manual loops, fear-based restrictions

4.1 Decision Impact (Q)

Decision impact refers to measurable improvements in predictive accuracy, risk assessment, strategic alignment, and error reduction attributable to AI deployment. Examples include improved demand-forecast accuracy, enhanced credit risk scoring, more precise dynamic pricing algorithms, and AI-augmented clinical diagnosis. Decision impact is meaningfully distinct from activity metrics such as the number of AI tools deployed or the volume of prompts processed. The critical diagnostic question is: Where is AI measurably improving decision quality?

Required evidence includes error-reduction rates, forecast-accuracy uplift, risk-adjusted return improvements, and pricing-precision gains. A pervasive organizational failure is the substitution of AI adoption metrics for decision-quality metrics: reporting the percentage of employees using Copilot tools rather than the percentage improvement in decision quality attributable to those tools. This substitution systematically obscures whether AI is generating value.

Hypothesis 1

AI-induced improvements in decision impact (Q) are positively associated with firm-level financial performance, as measured by EBITDA margin and return on assets.

4.2 Decision Velocity (S)

Decision velocity captures reductions in the cycle time for consequential strategic and operational decisions. AI may compress time-to-market for new products, accelerate credit or insurance underwriting approvals, shorten supply chain response times to demand shocks, or reduce the elapsed time between risk identification and executive decision-making. In each case, the value driver is not speed per se but the reduction of organizational latency—the gap between information availability and decision execution.

Critically, decision velocity improvements are frequently blocked not by information processing limitations—which AI can address—but by unchanged decision rights and approval structures. A common pattern is AI pilots that demonstrably accelerate information synthesis while decision rights remain centralized, and approval chains remain intact. In this configuration, AI reduces the time to prepare a recommendation but does not reduce the organizational latency of the final decision. This constitutes a red flag: AI capability without redesign of authority.

Hypothesis 2

AI-induced reductions in decision latency (S) are positively associated with revenue growth and cost efficiency. However, this association is moderated by the degree of concurrent redesign of decision rights and authority structures.

4.3 Decision Scale (L)

The decision scale reflects the volume and granularity of decisions executed within a given time period. AI uniquely enables mass personalization, automated portfolio adjustments, large-scale scenario simulation, and real-time dynamic pricing—decision categories that were previously economically infeasible at scale. The value of decision scale is most clearly visible in customer-facing contexts: AI enables firms to make individually optimized pricing, product, and service decisions across millions of interactions simultaneously.

A key diagnostic is whether AI is deployed in revenue-generating decision processes or confined to internal productivity applications. AI tools used only for document summarization, email drafting, or internal knowledge retrieval do not expand the decision-making scale in an economically meaningful sense. They may reduce cognitive overhead, but do not structurally increase the volume or quality of decisions that affect competitive positioning. Amazon's thirty-year investment in operational productivity—continuously reinvesting margins into decision-scale expansion, including AWS, recommendation systems, and dynamic pricing—illustrates the long-term compounding effect of decision-scale strategy.

Hypothesis 3

The expansion of the AI-enabled decision scale (L) is positively associated with competitive differentiation, particularly in markets where personalization, speed, and adaptive pricing are primary competitive dimensions.

4.4 Coordination Burden (CC₁)

Coordination cost includes integration complexity, additional oversight layers, human-in-the-loop validation requirements, and cross-functional friction introduced by AI systems. A critical insight of the AIVF is that AI adoption routinely generates coordination overhead that is underweighted in project planning and ROI analysis. New AI deployments frequently require governance committees, model review boards, data stewardship structures, integration project management, and risk escalation protocols, all of which consume substantial managerial attention.

The diagnostic indicator is straightforward: if AI adoption has led to the creation of three new oversight committees, four additional review layers, and a proliferation of shadow governance structures, V_{ai} is likely declining even if the AI models themselves are technically performing well. Coordination costs must be measured as rigorously as productivity gains. Indicators include the number of new committees created, the number of review layers added, and the complexity of cross-functional approval chains relative to pre-AI baselines.

Hypothesis 4

Coordination cost (CC₁) moderates the relationship between AI investment and firm performance such that high coordination burden reduces or eliminates net AI value, holding decision productivity constant.

4.5 Governance Efficiency (GC₂)

Governance cost encompasses compliance monitoring, model auditing, ethical oversight, regulatory adherence, data quality assurance, and accountability structures associated with AI deployment. Governance is necessary: AI systems that operate without adequate oversight expose firms to legal liability, reputational harm, regulatory sanction, and catastrophic failure modes (Russell, 2019; Cath, 2018). However, governance exhibits diminishing marginal returns and may exhibit an inverted-U relationship with AI value.

Embedded controls, automated monitoring, and risk-weighted oversight proportionate to the stakes of specific AI applications characterize healthy governance. Unhealthy governance is characterized by blanket approval requirements, uniform manual review loops regardless of risk level, and fear-based restrictions that apply precautionary logic regardless of calibrated empirical risk. The latter pattern—which we term “governance theater”—is as damaging to AI value as the absence of governance and is arguably more common in large incumbent organizations. Governance that blocks experimentation and iteration forfeits the adaptive advantage that AI could provide.

Hypothesis 5

Governance cost (GC₂) exhibits an inverted-U relationship with AI value: insufficient governance increases risk and the probability of catastrophic failure. In contrast, excessive governance reduces economic returns by blocking execution and fostering organizational inertia.

5. The AI Value Quadrant

The AIVF predicts four structural regimes based on the joint profile of decision productivity and organizational cost. Table 2 presents these regimes and their strategic implications.

Table 2. AI Value Quadrant

Decision Productivity	Coordination & Governance Cost	Outcome	Strategic Implication
Low	Low	Cosmetic AI	No competitive impact

High	High	Bureaucratic AI	Value neutralized by overhead
Low	High	Value Destruction	Net negative return
High	Controlled	Structural Advantage	Sustained competitive

Cosmetic AI describes firms in which both decision productivity and organizational cost are low. AI has been deployed but is confined to low-stakes internal productivity applications. The firm is not generating a competitive advantage from AI, but is also not experiencing significant value destruction. This is the modal state of large organizations in the early phases of AI adoption.

Bureaucratic AI describes the most common failure mode among firms that have invested seriously in AI. Decision productivity improvements exist—forecasting is more accurate, pricing is more granular, risk assessment is faster—but they are largely offset by the governance structures, coordination overhead, and integration complexity introduced to manage AI at scale. Value is neutralized rather than captured. This is Strassmann's IT paradox instantiated in the context of AI.

Value Destruction describes the worst-case scenario: AI has increased organizational complexity and costs while failing to improve decision quality or velocity. This occurs when AI is deployed without complementary organizational change, when AI systems generate information that decision-makers lack the authority or incentive to act upon, or when governance structures are so restrictive that AI-enabled insights cannot be implemented. This regime is rare but consequential.

Structural Advantage describes the target state. Decision productivity is high across all three dimensions, and organizational cost is controlled through proportionate governance and simplified coordination. Only this regime produces a sustained competitive advantage. Achieving and maintaining it requires continuous organizational redesign, not merely technological deployment.

6. The AI Maturity Ladder

Organizations progress toward structural advantage along a maturity continuum. Table 3 characterizes four levels of AI organizational maturity, reflecting the degree to which AI is integrated into consequential decision systems.

Table 3. AI Organizational Maturity Ladder

Level	Stage	Characteristics	Board Priority
0	Experimental	Scattered pilots; no enterprise metrics	Establish baseline measurement

1	Tool Adoption	Copilots deployed; productivity narrative dominant	Link tools to decision KPIs
2	Embedded Intelligence	AI linked to decision domains and measurable outcomes	Redesign workflows around AI
3	AI-Native Operating Model	Workflow redesign, agentic systems, structural advantage	Sustain and extend the competitive moat

At Level 0 (Experimental), AI activity is characterized by scattered pilots with no enterprise metrics, ad hoc governance, and no systematic linkage between AI outputs and business decisions. The majority of organizational AI investment at this level produces learning value but negligible economic return.

At Level 1 (Tool Adoption), AI tools such as copilots and generative assistants are widely deployed, but the dominant narrative focuses on individual productivity. Decision rights remain unchanged, workflow structures are not redesigned, and AI outputs feed into existing approval processes without structural modification. This is the modal state of Fortune 500 AI programs in 2025.

At Level 2 (Embedded Intelligence), AI is explicitly linked to defined decision domains with measurable KPIs. Forecast accuracy, approval cycle time, pricing precision, and risk assessment quality are tracked and reported relative to AI inputs. Organizational structures begin to reflect AI capabilities: decision rights are adjusted, feedback loops are formalized, and governance is proportionate to decision stakes.

At Level 3 (AI-Native Operating Model), AI is structurally embedded in core operational and strategic processes. Agentic systems operate with defined accountability structures, workflow redesign has occurred around AI capabilities, and incentive systems have been updated to reflect AI-enabled decision boundaries. This level represents a genuine structural advantage—the organizational architecture itself becomes difficult to replicate. Board responsibility should be explicitly framed as accelerating the progression from Level 1 to Level 3.

7. Empirical Strategy

The AIVF generates a set of testable hypotheses amenable to empirical investigation through multiple methodological approaches.

Cross-sectional firm-level analyses can test the basic value condition by examining whether firms with higher ratios of decision productivity to coordination and governance cost outperform on financial metrics (ROA, EBITDA margin, revenue growth). Construct operationalization requires: (i) decision impact measures such as forecast accuracy uplift, error reduction rates, and risk-adjusted return improvements; (ii) decision velocity measures such as

time-to-decision metrics for defined decision categories; (iii) decision scale measures such as the volume of AI-enabled customer-level decisions; (iv) coordination cost proxies such as compliance headcount growth, new committee formation, and approval chain complexity indices; and (v) governance cost proxies such as audit expense, model review frequency, and regulatory compliance expenditure.

Panel data on longitudinal AI deployment and organizational redesign can assess whether firms that redesign decision rights concurrent with AI deployment (capturing velocity and scale benefits with controlled coordination costs) generate superior returns relative to firms that deploy AI without structural change. Structural equation modeling is well-suited to test the proposed mediation structure (AI investment → decision productivity → firm performance) and the moderation structure (coordination and governance cost moderating the investment-performance relationship).

At the industry level, the variance amplification proposition (Proposition 2) predicts that within-industry performance dispersion will increase following widespread AI adoption. This prediction can be tested using panel data on firm performance across industries at varying stages of AI penetration, analogous to Brynjolfsson and Hitt's (2000) analysis of IT and productivity dispersion.

Natural experiments may be identified through regulatory events (GDPR, AI Act enforcement), major model capability transitions (the release of large language models at specific capability thresholds), or firm-specific reorganizations that altered decision architectures independent of AI capability changes.

8. Implications for Strategy

8.1 AI Spending Is Not AI Value

The most consequential managerial implication of the AIVF is the disconnection between AI expenditure and AI value. Strassmann's (1990) original finding—that IT spending per employee showed no consistent correlation with profitability—appears to be replicating in the AI context. Firms with large language model subscriptions, GPU cluster investments, and Copilot licenses deployed across every department are not systematically outperforming firms with focused, structurally integrated AI deployments. AI expenditure per employee is not a reliable predictor of firm-level performance; V_{ai} is.

This has direct implications for capital allocation. Boards and executive teams that evaluate AI investment based on deployment scale—the number of deployed tools, the number of employees with access, and the number of pilots launched—are measuring the wrong variable. The relevant question is not “How much are we spending on AI?” but “Is our AI increasing decision productivity faster than it is increasing coordination and governance burden?”

8.2 The New Productivity Paradox

The structural dynamics of the current AI deployment wave parallel Strassmann's IT productivity paradox with notable fidelity. AI capability is advancing exponentially across

benchmarks, yet enterprise productivity gains remain modest in aggregate. The explanation offered by the AIVF is consistent with Strassmann's original diagnosis: most firms are adding AI as a layer on top of existing organizational structures rather than redesigning those structures around AI capabilities. Decision rights remain unchanged. Approval chains remain intact. Governance structures are additive rather than redesigned. AI becomes an expensive assistant operating inside a bureaucratic structure rather than a structural enabler of superior decisions.

The implication is that organizational architecture is the binding constraint on the creation of AI value. Model performance is rarely the bottleneck; organizational design is. Firms that recognize this shift their investment focus from model procurement to architecture redesign—a fundamentally different strategic posture.

8.3 AI as Variance Amplifier

Proposition 2 has strategic implications that extend beyond individual firms. AI functions as a variance-amplifying technology at the industry level: it compounds competitive advantage for well-organized firms and compounds dysfunction for poorly organized ones. This implies that industries in the early stages of AI adoption are likely to experience increasing performance dispersion, a concentration of gains among a small number of leaders, and an accelerating gap between the leaders and the median firm.

For competitive strategy, this suggests that the cost of organizational inertia—delaying structural redesign while deploying AI cosmetically—is not zero; it is active deterioration relative to leading firms that are compounding structural advantage. The strategic urgency of moving from Level 1 to Level 3 on the maturity ladder is therefore greater than it might appear from any static snapshot of current performance gaps.

8.4 Agentic AI and the Authority Boundary

The transition from AI as a tool (augmentation) to AI as an agent (autonomy) introduces a qualitatively distinct governance challenge. Agentic AI systems—those capable of taking sequences of actions, calling external tools, and making decisions within defined parameters without continuous human approval—are rapidly becoming deployment-ready. The value potential of agentic AI is substantial. For the first time, AI can compress decision cycles and expand decision scale simultaneously, without the human latency that limits tool-based augmentation.

However, autonomy without governance is, as we term it, “digital anarchy.” The conditions for safe and value-generating agentic deployment are organizational, not technological: clear authority structures specifying the domains within which agents may act; accountability mechanisms capable of auditing agent decisions post hoc; feedback loops that surface errors rapidly; and incentive systems aligned to decision quality rather than decision volume. Firms that deploy agentic AI without redesigning authority structures and accountability mechanisms are manufacturing coordination risk at scale.

9. Implications for Corporate Governance

9.1 The Board's Decision Productivity Mandate

Boards of directors have typically approached AI governance through a risk lens, focusing on model bias, data privacy, regulatory compliance, and reputational exposure. The AIVF suggests that this framing, while necessary, is insufficient. Risk-only governance systematically underweights the opportunity cost of excessive caution and additive oversight. Boards should evaluate AI through a dual lens—risk management and decision productivity—and should hold management accountable for quantifiable improvements in V_{ai} .

The core board-level diagnostic questions are: (i) Is AI measurably improving decision impact across our primary value-creation domains? (ii) Has AI compressed decision cycle times materially, or do unchanged decision rights negate the velocity potential? (iii) Has AI expanded decision scale in revenue-generating processes, or is it confined to internal productivity? (iv) Are coordination costs trending down, stable, or rising? (v) Is governance proportionate to risk, or has it become a structural barrier to AI value?

If management cannot provide quantitative answers to these questions, AI governance is at Level 0 or Level 1, regardless of the sophistication of the deployed AI models.

9.2 Coordination as the Persistent Cost Center

A persistent insight from organizational economics is that firms are fundamentally coordination systems. The economic value of firm boundaries derives from their comparative efficiency at coordinating productive activity relative to markets. AI does not eliminate this coordination challenge; it transforms it. AI can now draft complex documents, analyze large repositories of contracts, and synthesize multi-source market signals in real time. However, the organizational bottleneck has not shifted to information processing—it has remained in alignment, approval chains, risk control, and incentive reconciliation.

If AI increases information flow but decision rights remain centralized, and accountability structures remain unchanged, coordination complexity increases rather than decreases. More information reaching the same approval chains increases review burden, not leading to faster decisions. The organizational implication is that AI value is contingent on parallel investment in coordination architecture: clarifying decision rights, reducing approval chain length, automating monitoring where feasible, and aligning incentives to AI-enabled decision boundaries.

9.3 Strategic vs. Cosmetic AI

A critical board-level judgment is the distinction between cosmetic and strategic AI deployment. Cosmetic AI applications—internal chatbots, slide generation, meeting summarization, marketing copy production—produce what might be termed “productivity theater”: visible AI activity that generates modest individual efficiency gains without altering the decision systems that drive competitive position. These applications are not without value, but they are categorically different from structural AI applications.

Strategic AI applications are those embedded in core revenue-generating or cost-determining decision processes: AI-native pricing models, real-time risk engines, autonomous supply chain optimization, personalized product architecture, and AI-driven capital allocation. Only structural AI changes industry economics. Boards should demand explicit categorization of AI initiatives along this dimension and should evaluate capital allocation accordingly.

9.4 Governance Architecture Over Model Selection

Much executive and board attention is currently directed at model selection: GPT-5 versus Claude versus Gemini; open versus closed models; fine-tuning versus retrieval-augmented generation. The AIVF suggests that this attention is largely misplaced. Model choice is secondary; governance architecture is primary. The determinants of AI value are organizational, not computational: clarity of decision ownership, model auditability, feedback-loop integrity, incentive alignment, and data-quality discipline.

A firm with mediocre models embedded in a well-designed decision architecture will systematically outperform one with state-of-the-art models embedded in a poorly designed decision architecture. The model is rarely the constraint. Boards and executive teams that allocate disproportionate attention to model capability rather than governance architecture are solving the wrong problem.

10. Discussion

The AIVF integrates managerial productivity theory (Strassmann, 1990), transaction cost economics (Coase, 1937; Williamson, 1985), and research on general-purpose technology (Bresnahan & Trajtenberg, 1995; Brynjolfsson & McAfee, 2014) into a unified framework for analyzing AI value creation. Several theoretical contributions and limitations warrant discussion.

The framework's most significant theoretical contribution is its reframing of AI as an organizational architecture intervention rather than a technological artifact. This reframing resolves the apparent paradox of divergent outcomes from comparable AI investments: the relevant variable is not the AI system but the decision architecture into which it is embedded. This is consistent with Milgrom and Roberts' (1990) thesis of organizational complementarities, which holds that the value of individual organizational practices depends on their fit with other practices in the system. AI is not a standalone practice; it is a complement to (or substitute for) existing decision-making structures.

A second contribution is the introduction of governance efficiency as a moderating variable with a non-monotonic relationship to AI value. The literature on AI governance has largely treated governance as a constraint to be satisfied (e.g., EU AI Act compliance requirements) rather than as a variable with an optimal level. The AIVF predicts that both insufficient and excessive governance destroy value, implying that governance design is itself a source of competitive differentiation.

The framework has several limitations. First, it is static: it models AI value at a point in time rather than capturing the dynamic evolution of AI capabilities and organizational

responses. A dynamic extension would model how firms learn, adapt governance structures, and redesign decision architectures in response to AI deployment experience. Second, the constructs, while theoretically grounded, require extensive operationalization work before large-sample empirical testing. Third, the framework is primarily applicable to business-value contexts; extensions to public sector, non-profit, and regulatory contexts would require modification.

11. Conclusion

The central argument of this paper is that AI does not create economic value solely by virtue of its computational capabilities. It creates value when it increases the productivity of decision systems faster than it increases organizational friction. This conclusion—an extension of Strassmann's (1990) managerial productivity thesis to the AI context—carries significant implications for how firms deploy AI, how boards govern it, and how researchers study it.

The AIVF formalizes AI value creation as a function of decision impact, decision velocity, and decision scale relative to coordination and governance costs. This formulation generates testable hypotheses, a diagnostic framework for organizational self-assessment, and a maturity ladder charting the path from cosmetic AI deployment to structural competitive advantage. The framework predicts increasing within-industry performance variance as AI adoption matures, firms with strong organizational architecture compound advantage, while poorly organized firms compound dysfunction.

The deepest implication of the framework is that the AI era demands a new conception of organizational capability. The question that defines competitive position is not “How advanced is our AI?” but “Is our organization architected to convert intelligence into economic value?” Answering this question requires organizational redesign, governance proportionality, and the discipline to measure the productivity of decisions rather than AI activity. Future empirical research should test the proposed hypotheses, examine how AI-native operating models reshape industry structure, and investigate the dynamic processes by which firms move along the maturity ladder.

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