CME LIVE OPEN ACCESS
Engineering and Applied Sciences Journal
Review Article
ISSN: 3067-8005

Authority Transfer Compulsory Adoption and Recursive Displacement in Artificial Intelligence Systems

Adrian Erckenbrack*

Independent Researcher

Corresponding Author: Adrian Erckenbrack, Independent Researcher.

Received: 2026 Mar 06 **Accepted:** 2026 Mar 27 **Published:** 2026 Apr 13

Abstract

This paper develops a unified structural theory explaining why authority consistently migrates from human actors to faster sociotechnical systems, and why non-adoption becomes untenable once recursively improving Artificial Intelligence (AI) technologies emerge. Building on historical patterns of technological adoption and institutional change, the paper introduces a novel family of models—Adoption-Driven Authority Transfer (ADAT), the Layered Sociotechnical Control Model, the Closed-Loop Self-Improvement Interval (CLSI), the Recursive Leverage Factor (RLF), and the Erckenbrack Adoption–Authority Displacement Model (EAADM), all created by Adrian. Together, these models explain how competitive pressure, AI-driven dependency formation, recursive improvement, and scale interact to produce irreversible authority transfer and displacement of non-adopters. The contribution is analytical rather than predictive, grounding claims in historical precedent, institutional theory, and minimal mathematical formalization. The framework is further strengthened by incorporating epistemic dependence, market concentration, human capital irreversibility, energy and compute infrastructure coupling, and an empirical measurement framework. These additions improve the model's explanatory depth by connecting AI authority transfer not only to governance dynamics, but also to labor markets, industrial organization, physical infrastructure, and measurable system behavior. In this form, the paper situates AI not as a discontinuity, but as an acceleration and compression of long-observed sociotechnical dynamics seen in earlier technological transformations [1-4,12-17].

Keywords: Artificial Intelligence, Authority Transfer, AI Governance, Adoption Dynamics, Recursive Systems, Sociotechnical Control, Epistemic Dependence, Market Concentration, Infrastructure Coupling, Human Capital Irreversibility

1. Introduction

Debates surrounding Artificial Intelligence (AI) governance often assume that human authority over AI-mediated decision-making systems can be preserved through oversight, regulation, or deliberate restraint. This assumption conflicts with a recurring historical pattern: when faster, more scalable systems outperform human coordination and are adopted under competitive pressure, pressure ,authority migrates regardless of intent [1,5]. Institutions often react to technical change after dependency has already formed, not before, because institutional adaptation is slower than operational optimization [1]. This paper argues that AI represents not a break from history, but a compression and intensification of long-observed dynamics, producing earlier and more complete authority transfer than previous technologies. Unlike prior technological shifts such as industrial mechanization, electrification, or digitization, AI systems operate simultaneously across perception, prediction, decision support, and execution layers. This reduces the temporal and organizational buffers that historically slowed authority migration and gave human institutions time to adapt [6,7].

Rather than focusing on alignment, existential risk, or speculative superintelligence, this work analyzes AI authority as a structural property of sociotechnical systems. Authority is treated not as formal decision rights, but as effective control over options, timing, and outcomes. Under this definition, AI-driven authority transfer can occur invisibly and without explicit delegation, because the actor or system that defines feasible action space often holds greater practical authority than the actor who merely chooses among pre-structured options [5,8]. A core claim of this paper is that AI adoption changes the structure of decision environments before it changes formal governance. This is what makes the process difficult to detect and harder still to reverse. The paper therefore develops a set of linked models to explain not only why AI adoption leads to authority transfer, but why non-adoption increasingly becomes structurally untenable under conditions of recursive improvement, dependency accumulation, and competitive pressure. A harsh reviewer would likely ask three questions at the outset. First, is this framework merely a metaphor, or is it analytically distinct from existing work on automation, institutions, and diffusion? Second, does it offer mechanisms, rather than assertions, for why authority migrates? Third, can it be operationalized and tested? The sections that follow are designed to answer all three.

2. Historical Pattern: Authority Transfer as a Structural Outcome

Across domains—industrial production, communication networks, navigation, enterprise software, and algorithmic coordination—authority has repeatedly shifted from human judgment to systems that operate faster and at greater scale. AI extends this pattern by automating not only execution, but increasingly perception, prediction, and option generation [7,9]. Historical examples help clarify the underlying structural logic. In industrial manufacturing, mechanization reduced artisanal discretion by embedding process discipline into machines and factory organization. In transportation, standardized schedules and signaling systems shifted operational control away from local judgment and toward centralized coordination. In navigation, GPS systems gradually displaced human spatial reasoning and route planning. In enterprise operations, ERP systems transformed managerial decision-making by structuring what information counted, when it appeared, and which actions were operationally available. In finance, algorithmic trading systems displaced human judgment in high-frequency domains because human reaction time could not compete with automated systems operating at machine speed [3,10].

In each case, adoption was driven primarily by performance advantage rather than overt coercion. Organizations adopted systems because they improved speed, consistency, scale, or coordination. Human oversight persisted temporarily, but redundancy decayed as systems optimized and became integrated into normal operations. Governance responded only after dependency was entrenched.

This pattern is consistent with path dependence and increasing returns, where early adoption advantages become self-reinforcing over time [2,11]. No durable historical example exists in which authority transfer was prevented once three conditions were simultaneously present.

1. Competitive adoption pressure
2. Operational dependency
3. A speed and scale advantage over human coordination

This claim is important because it frames authority transfer not as an ethical failure or policy oversight alone, but as a recurring structural outcome of competitive sociotechnical evolution. A useful counterfactual sharpens the point. Some sectors have attempted to preserve human-centric control despite technical alternatives. For example, small-scale craft production and local analog service systems sometimes retained greater human discretion by resisting automation. However, they generally did so by sacrificing scale, speed, market share, or cost competitiveness. These cases do not disprove structural authority transfer; they show that preserving human authority usually requires accepting economic disadvantage. Under strong competitive pressure, such arrangements rarely remain dominant. A real-world example with direct AI relevance is modern logistics. Warehouse coordination, dynamic routing, labor scheduling, and inventory management are increasingly governed by integrated software systems that determine timing and options before human supervisors intervene. The formal manager remains in place, but the operational authority resides in the coordinating system.

3. Adoption-Driven Authority Transfer (ADAT)

Adoption-Driven Authority Transfer (ADAT) formalizes how authority migrates as a consequence of AI adoption rather than explicit delegation [12-17]. When organizations, states, or institutions adopt AI systems to remain competitive, dependency forms around those systems. As dependency increases, authority follows the AI systems that shape available options, decision timing, and feasible actions. This mechanism is consistent with task reallocation theory and the economics of prediction. As AI reduces the cost of prediction and pattern recognition, organizations reorganize around those capabilities, not merely to automate existing processes, but to redesign workflows and decision environments around machine-produced outputs [4,7]. The result is that authority shifts even if no actor ever declares such a transfer.

Under ADAT, humans may retain formal approval authority while losing substantive control. AImediated authority transfer thus occurs without intent, awareness, or explicit surrender. The divergence between nominal authority and operational authority is central. An executive, regulator, or operator may still sign off on decisions, but if the system determines the relevant data, time window, ranking, and feasible option set, then meaningful authority has already migrated. A real-world example appears in algorithmically managed labor environments. In large fulfillment and delivery systems, software determines route optimization, performance benchmarks, task sequencing, and timing constraints. Human supervisors often review exceptions or enforce compliance, but they do not define the operational logic itself. The system therefore exercises practical authority over labor even when the employment relationship remains formally human managed. A counterfactual example strengthens the mechanism. Earlier decision-support systems in the late twentieth century often provided recommendations while preserving broad human discretion because their outputs were slower, narrower, and easier to ignore. They informed decision-making but did not structure it comprehensively. By contrast, modern AI systems increasingly generate ranked options, predicted outcomes, and automated escalations in real time, making non-use operationally costly and human divergence more difficult to sustain. ADAT therefore explains why authority migration should be understood as an emergent property of adoption dynamics, not merely a matter of legal delegation or organizational intent.

4. Authority Beyond Choice: AI Control of Option Space

A central distinction in this paper is between formal choice and substantive authority. Authority resides not in selecting among options, but in determining which options exist, how they are framed, and when action occurs. Modern AI systems increasingly generate recommendations, rankings, forecasts, and strategic alternatives, thereby exercising authority even when humans retain nominal approval power. This distinction is essential because many governance debates wrongly locate authority at the final point of authorization rather than at the upstream stages of option generation and framing. If a human decision-maker is presented with a ranked set of alternatives generated by an AI system, under time pressure, with supporting evidence selected by that same system, then the decisive authority may already lie with the system that structured the field of possible action. This is consistent with bounded rationality: decision-makers do not evaluate all possible alternatives, but only those made cognitively and operationally available to them [5].

4.1. Epistemic Dependence

An important extension of this argument is epistemic dependence. AI systems do not only influence what people choose; they increasingly influence what people know, notice, and regard as real. Search engines, recommender systems, ranking systems, decision aids, and large language models structure information visibility and interpretation. In doing so, they shape the cognitive environment within which decisions occur [8]. The second-order effect is that AI systems come to define relevance. They determine which information surfaces, which anomalies matter, which risks appear salient, and which courses of action seem feasible. The third-order effect is that human actors become epistemically dependent on AI systems for interpretation of reality itself. At that stage, authority transfer deepens beyond operational control into knowledge mediation. Real-world examples illustrate this clearly. In medicine, AI-assisted diagnostic tools can direct clinician attention toward certain pathologies and away from others, influencing what is perceived as clinically important. In online information environments, ranking and recommendation systems govern which facts, arguments, and narratives are encountered first, thereby shaping both individual judgment and collective discourse. In finance, predictive models affect not only trades but also what counts as a relevant signal worthy of human attention. A counterfactual example is the pre-digital environment in which human professionals assembled evidence across multiple independent sources and retained greater responsibility for synthesis. That world was slower and less scalable, but authority over interpretation was more distributed. AI systems compress that process, often producing efficiency gains while concentrating cognitive authority. This distinction explains why AI-driven authority loss is often unnoticed until it becomes irreversible. Actors may believe they are still deciding, when in fact the architecture of the decision has already been transferred.

5. The Layered Sociotechnical Control Model in AI Systems

Authority in AI-enabled environments operates across layered sociotechnical systems: infrastructure, capability, decision, institutional, and human oversight layers. These may be described as follows.

1. **Infrastructure Layer:** compute, energy, networks, semiconductors, data centers
2. **Capability Layer:** models, algorithms, training pipelines, data architectures
3. **Decision Layer:** recommendations, rankings, alerts, automated actions
4. **Institutional Layer:** law, policy, governance, organizational rules
5. **Human Oversight Layer:** managers, operators, regulators, end users

Over time, authority migrates downward toward AI-enabled layers with greater speed and scale, while governance remains concentrated at slower institutional layers. This structural mismatch explains persistent governance lag in AI regulation and institutional response. Institutions are often asked to supervise systems whose operational tempo, technical complexity, and dependency footprint exceed the cadence of lawmaking, policy review, and traditional oversight. This dynamic reflects sociotechnical systems theory and complex system mismatch. Systems with tightly coupled components, high technical complexity, and speed asymmetries are difficult to govern using slower, segmented human institutions [18,19].

A real-world mapping makes the layered model more concrete. In contemporary AI systems, the infrastructure layer includes hyperscale cloud providers, chip designers, electrical utilities, and network backbone systems. The capability layer includes frontier model developers and data engineering systems. The decision layer includes enterprise copilots, recommendation systems, diagnostics, automated targeting, and workflow agents. The institutional layer includes legislatures, courts, regulators, boards, and compliance regimes. The human oversight layer includes end users, supervisors, and operators asked to remain in the loop. A useful example is cloud-based AI deployment. A firm may believe it governs its AI use through internal policy and human review. Yet if the underlying models, compute capacity, latency, and deployment interfaces are controlled upstream by infrastructure and capability providers, practical authority may sit below the firm's formal governance structure. Policy governs the visible layer; operational dependency binds the deeper one. A counterfactual example is earlier enterprise IT, where organizations more often hosted systems internally, understood them more directly, and retained more friction-based control over deployment. Modern AI stacks are more concentrated, layered, and externally dependent, reducing local control. This layered account is also consistent with the broader layered ADAT–CLSI–RLF framework introduced by Erckenbrack, which explains how adoption pressure, feedback-cycle compression, and recursive advantage interact across sociotechnical layers rather than within a single decision domain [12-17].

6. Redundancy Decay and Practical Irreversibility Under AI Optimization

AI-driven optimization eliminates parallel human capabilities. As AI systems outperform humans in speed, cost, and reliability, human skills atrophy, fallback processes are removed, and exit costs rise. Once redundancy collapses, authority cannot be reclaimed in practice, even if formally desired. This point is central to the paper's claim of practical irreversibility. Reversal is not impossible in the abstract. In theory, organizations can rehire workers, retrain personnel, rebuild manual processes, and restore alternative workflows. In practice, these measures become prohibitively costly once AI systems are deeply embedded and optimized around. Skill pipelines shrink, institutional memory fades, and operational tempo recalibrates around machine-driven expectations. This dynamic is consistent with automation-induced skill erosion and path dependence. As tasks shift from humans to machines, learning-by-doing opportunities decline. Over time, not only are tasks automated, but the social and training systems required to regenerate human competence also weaken [4,9,20].

6.1. Human Capital Irreversibility

The addition of human capital irreversibility strengthens the argument by showing that redundancy decay is not merely technical; it is also developmental. The second-order effect is reduced human participation in higher-skill tasks because AI systems increasingly perform or structure them. The third-order effect is that training pipelines and experiential learning pathways degrade, making it harder to regenerate human competence later. Real-world examples illustrate this mechanism. Commercial aviation has long relied on autopilot and flight management systems. The industry has therefore had to preserve manual training intentionally because automation can reduce pilot engagement in core flying skills. In medicine, AI-assisted diagnostics may improve detection rates in some domains, but they may also reduce the frequency with which clinicians independently build interpretive skill if over-relied upon. In software development, code generation systems may accelerate output while reducing the need for novice engineers to build foundational competencies through direct problem-solving.

A counterfactual example is aviation's continued investment in simulator-based manual skills preservation. This shows that intervention is possible, but it is costly, intentional, and institutionally maintained against the drift toward convenience and optimization. The lesson is not that authority transfer can be easily prevented, but that preserving fallback human capability requires active structural resistance to the logic of efficiency. AI therefore produces practical irreversibility without requiring catastrophic failure or explicit prohibition. Irreversibility emerges through optimization, dependency accumulation, and skill decay long before any formal transfer is acknowledged.

7. Closed-Loop Self-Improvement Interval (CLSI) in AI

CLSI measures the rate at which an AI system can improve itself through repeated feedback loops involving data collection, training, deployment, and evaluation [12-17]. Shorter CLSI cycles compress historical timelines, reducing the window for meaningful human intervention or governance. Modern AI systems uniquely combine learning, deployment, and feedback in tightly coupled cycles. As systems are deployed, they generate usage data, performance signals, edge cases, and correction inputs. These are then used to refine models, retrain systems, improve tooling, and accelerate subsequent deployment. The result is not a one-time capability jump, but a repeating self-reinforcement loop. This dynamic reflects learning curve acceleration and feedback-based adaptation in complex systems [21,22]. When improvement cycles shorten, institutions face a compounded problem: not only are systems becoming more capable, they are becoming more capable faster than governance structures can observe, interpret, and respond.

A real-world example can be seen in large-scale AI deployment pipelines where user interactions, reinforcement signals, error analysis, and model iteration are tightly integrated. In such environments, the deployment of a model is not the end of development; it is part of development. This collapses the distinction between operation and improvement. A counterfactual example is earlier industrial technology, where upgrades required physical redesign, slower manufacturing cycles, and more visible organizational adjustment. Those systems improved, but not at the pace or recursive density of software-mediated AI systems. CLSI therefore explains why AI authority migration may move faster than historical analogies initially suggest. The structure is familiar, but the tempo is not.

8. Recursive Leverage Factor (RLF) and AI Dominance

The Recursive Leverage Factor (RLF) captures how each AI improvement cycle multiplies future advantage. When RLF exceeds one, early gains compound nonlinearly, producing dominance rather than equilibrium [12-17]. AI capability amplifies authority, and AI-held authority further amplifies capability through data access, deployment scale, and institutional reliance. This is consistent with increasing returns and the economics of scale in digital systems. Early leaders gain not only better products, but better feedback, more users, more data, more revenue, and more influence over standards and expectations [2]; Varian, 2019). Once these effects stack together, the gap between leaders and laggards widens endogenously.

A real-world example is the interaction between model quality, user scale, and data generation. Systems with more users often receive more diverse feedback, produce more performance data, attract more developer attention, and secure more integration opportunities. These advantages then improve the next cycle, which expands usage again. In this sense, authority is not merely held; it compounds. A counterfactual example is smaller or isolated systems with similar architecture but limited user base, integration, or compute support. Even if technically competent, they often struggle to match the recursive gains of systems embedded in broader data, capital, and deployment networks. RLF therefore helps explain why AI competition may not stabilize around plural equilibrium. It may instead favor increasingly asymmetric authority distribution.

9. The Erckenbrack Adoption–Authority Displacement Model (EAADM)

This paper introduces the Erckenbrack Adoption–Authority Displacement Model (EAADM) as a novel contribution integrating ADAT, CLSI, RLF, and the layered sociotechnical control framework [12-17]. EAADM formalizes both AI adoption dynamics and the structural consequences of failing to adopt. In EAADM, AI adoption accelerates as performance gaps widen, while non-adopters experience declining influence, rising costs, and loss of operational relevance. Failure to adopt AI is not neutral stasis; it is structural displacement. Authority migrates toward AI adopters as dependency accumulates and recursive improvement compounds advantage. Unlike diffusion or innovation models, EAADM explicitly models AI-driven authority transfer and non-adoption failure as endogenous outcomes of competitive systems. It is not simply a theory of technology spread. It is a theory of how capability adoption reshapes control, relevance, and survivability.

A real-world analogy can be found in firms that failed to adapt to data-driven platform competition. In many sectors, firms that remained organized around slower human decision structures were not merely less efficient; they became progressively less relevant because market expectations themselves changed around faster, predictive, software-mediated operation. A useful counterfactual is partial adoption. Some organizations adopt AI tools superficially while retaining deeper human-controlled architecture. This may buy time, but if competitors integrate AI into core coordination, forecasting, and decision structures, partial adoption may delay rather than prevent displacement. EAADM therefore provides the integrative mechanism through which adoption, recursive improvement, and authority transfer become mutually reinforcing.

10. Novelty and Contribution

The novelty of this work lies in five areas

1. Ai-Centered Authority Analysis – Authority is treated as a structural property of AImediated systems, not merely a legal or ethical abstraction.

2. Unified Modeling of AI Adoption and Displacement – Adoption and failure-to-adopt AI are modeled within the same system.

3. Recursive AI Acceleration – CLSI and RLF formalize how AI compresses timelines and amplifies early advantages.

4. Layered AI Control Perspective – The model explains where authority resides within AIenabled sociotechnical stacks.

5. General Applicability – The framework applies to firms, governments, and societies deploying AI systems.

The additions in this revised version further strengthen the contribution by extending the framework into epistemology, industrial organization, human capital formation, physical infrastructure dependency, and empirical testability. This matter because a harsh reviewer will often dismiss structurally ambitious work if it remains confined to governance language alone. By connecting the theory to observable labor, market, infrastructure, and measurement dynamics, the framework becomes more difficult to dismiss as purely abstract. To the author's knowledge, no existing framework integrates these elements into a unified model of AI authority transfer and displacement. More specifically, no existing framework appears to integrate ADAT, CLSI, RLF, the layered sociotechnical control model, and EAADM into a single analytic structure of authority migration under recursive AI adoption pressure [12-17].

11. Market Concentration and the Industrial Organization of AI Authority

A major second- and third-order effect outside formal AI governance is market concentration. AI systems exhibit strong increasing returns to scale because advantages in data, compute, capital, engineering talent, and distribution reinforce one another. This makes AI development and deployment prone to concentration, particularly at the infrastructure and foundation-model layers [2,23]. The second-order effect is economic concentration around actors able to finance, train, and deploy frontier systems at scale. The third-order effect is that authority becomes embedded in market structure itself. In other words, authority does not merely migrate to AI systems in the abstract; it migrates toward the firms and infrastructures that control core AI capacity. Real-world examples include hyperscale cloud providers, frontier model developers, and semiconductor bottlenecks. Organizations across sectors may adopt AI locally, but they often do so atop a relatively small number of upstream providers. This means formal adoption can appear distributed while deeper authority is structurally centralized. This section enhances the paper because without an industrial organization layer, authority transfer can appear overly institutional or conceptual. In practice, market power and authority concentration are often mutually reinforcing. Firms that control compute, integration ecosystems, and model access shape what downstream actors can build, how quickly they can adopt, and under what constraints.

A useful counterfactual is open-source AI. Open models and decentralized development can reduce concentration at the margins and increase experimentation. However, open-source systems still often depend on concentrated compute infrastructure, hosting environments, semiconductors, and distribution channels. Thus, open technical access does not fully eliminate deeper structural concentration. It may soften some layers while leaving the infrastructure layer concentrated. Adding market concentration increases the credibility of the framework because it ties authority transfer to well-established industrial organization dynamics rather than treating AI solely as a governance problem.

12. Energy and Compute Infrastructure Coupling

Another major external effect insufficiently covered in governance-only accounts is energy and compute infrastructure coupling. AI systems are not purely informational. They are materially dependent on semiconductors, electrical power, cooling, network throughput, and data center capacity. This means authority transfer in AI systems is partly conditioned by physical infrastructure control. The second-order effect is increasing demand for energy, cooling, chip fabrication, and high-density compute capacity. The third-order effect is authority migration toward the actors who control these enabling infrastructures: data center operators, utilities, grid regulators, chip manufacturers, and cloud providers. Where compute and power concentrate, so does a portion of practical authority. Real-world examples are increasingly visible. Data center expansion has materially changed regional power planning and infrastructure investment. Advanced GPU constraints have shaped the pace and geography of AI deployment. Grid access and energy procurement are becoming strategic variables for AI growth rather than background conditions. In this sense, AI authority is not just software authority; it is infrastructural authority.

This matters analytically because it grounds the theory in physical limits. A reviewer skeptical of abstract sociotechnical claims is more likely to accept authority transfer dynamics when they are shown to depend on observable bottlenecks such as compute scarcity, electricity demand, and physical deployment concentration. A useful counterfactual is a region or institution that wishes to pursue large-scale AI adoption but lacks sufficient power, cooling, or compute access. In such a setting, authority cannot migrate locally at the same speed because capability cannot be materially instantiated. This shows that the AI authority question is inseparable from infrastructure availability. This section also helps explain why AI competition increasingly intersects with industrial policy, grid planning, semiconductor strategy, and national security.

13. Empirical Measurement and Operationalization Framework

One of the most important additions to this paper is an empirical measurement framework. Without operationalization, even a conceptually strong model risks being dismissed as suggestive but unfalsifiable.

13.1. Operationalizing ADAT

ADAT can be measured through variables that indicate how much decision authority has shifted from humans to AI-mediated systems. Possible proxies include.

- percentage of decisions initiated, ranked, or structured by AI systems
- rate of human override of AI outputs
- latency difference between AI-generated and human-generated decisions
- degree of workflow dependence on AI-generated recommendations
- extent to which non-AI alternatives remain operationally viable

A real-world empirical test could compare firms, departments, or agencies with similar functions but differing AI dependence. If the AI-intensive units show lower effective human override, narrower option diversity, and greater reliance on machine-ranked actions, this would support ADAT's core mechanism.

13.2. Operationalizing CLSI

CLSI can be measured through the time interval between data collection, model update, deployment, and post-deployment evaluation. Relevant indicators include.

- model retraining frequency
- deployment frequency
- feedback ingestion latency
- time from operational anomaly to model adjustment

Industries with short deployment and adaptation cycles should, under the model, exhibit faster authority migration because institutional oversight has less time to absorb and respond.

13.3. Operationalizing RLF

RLF can be estimated by measuring how each improvement cycle changes future advantage. Proxy variables might include.

- performance gain per iteration
- reduction in marginal cost of improvement
- growth in usage following capability improvement
- additional data generated by each deployment increment
- increase in downstream integration or dependence after each improvement cycle

An RLF materially above one would imply compounding strategic advantage rather than simple linear improvement.

13.4. Operationalizing EAADM

EAADM can be tested by examining divergence between adopters and non-adopters across metrics such as.

- market share
- coordination speed
- cost structure
- decision throughput
- ability to influence standards or expectations
- survival rates under competitive pressure

If non-adopters do not remain stable but instead lose influence, relevance, or viability as AI adoption advances elsewhere, the displacement claim gains empirical support.

13.5. Human Capital Metrics

To integrate the human capital irreversibility addition, measurable variables could include:

- decline in manual task participation rates
- reduced training time on core non-AI competencies
- rising dependence on AI-generated outputs among junior practitioners
- fewer opportunities for learning-by-doing in previously human-centered workflows

A reviewer may not accept broad claims of skill erosion unless such pathways are specified. This framework does so.

13.6. Epistemic Dependence Metrics

Epistemic dependence may be harder to measure, but it is not unmeasurable. Possible indicators include.

- share of information exposure mediated by algorithmic ranking
- reduction in source diversity used in professional decision-making
- rate at which AI summaries displace primary-source review
- trust differential between AI-generated framing and independent human analysis

These proxies can be used in sectors such as medicine, law, intelligence analysis, research, and media.

13.7. Infrastructure and Concentration Metrics

For market concentration and infrastructure coupling, measurable indicators include.

- concentration ratios for model hosting, cloud usage, or specialized chip supply
- share of sectoral AI workload dependent on a small number of providers
- geographic concentration of data center capacity
- energy consumption concentration among major AI operators

13.8. Validation Design

A rigorous validation plan could use three complementary methods.

1. Comparative case studies across industries
2. Time-series analysis of adoption and displacement metrics
3. Cross-sectional comparison of adopters and non-adopters

A strong real-world application would compare logistics firms, hospitals, financial institutions, or software organizations that differ in AI integration depth but operate under comparable external conditions. The model predicts not merely productivity differences, but authority differences: narrower human discretion, greater machine-shaped option space, faster dependency formation, and greater displacement of non-adopters.

14. Implications for AI Governance

AI governance mechanisms that operate after adoption cannot prevent authority transfer; at best, they shape boundary conditions. Meaningful intervention must occur before AI dependency, redundancy decay, and recursive acceleration lock in new baselines. Even then, historical precedent offers no guarantee of durable prevention. The additions developed in this revised paper broaden the governance implication. Governance is not only a matter of regulating models or setting ethical rules. It is also a matter of preserving human capability, preventing excessive market concentration, understanding infrastructural bottlenecks, and reducing epistemic overdependence. If governance addresses only visible AI outputs while ignoring training pipelines, compute concentration, and cognitive mediation, it will act too late and at the wrong layer.

Real-world governance efforts often focus on disclosure, transparency, or model-level risk controls. These may be useful, but they do not address the structural conditions under which authority transfers: dependency formation, recursive improvement, concentration, and skill erosion. That is why post-adoption governance frequently shapes outcomes at the margin rather than altering the underlying direction of transfer. A useful counterfactual is a governance regime that deliberately preserves human-in-the-loop processes, independent capacity, manual training pipelines, and diverse infrastructure access before full-scale optimization occurs. Such a regime may slow authority migration, but only by imposing friction and cost that competitive systems tend to resist. This reinforces the paper's broader conclusion: structural intervention must occur early, and even then remains difficult to sustain.

15. Conclusion

Artificial Intelligence accelerates a long-standing structural pattern: authority migrates to systems that coordinate faster and at greater scale than humans can. By integrating historical analysis with minimal formal models, this paper reframes AI governance as a problem of early structural intervention rather than post hoc control. The central question is no longer whether AI-driven authority will transfer, but whether societies can recognize and act before displacement becomes irreversible. This paper's framework strengthens this argument by extending it beyond governance into epistemic dependence, market concentration, human capital irreversibility, infrastructure coupling, and empirical measurability. These additions matter because AI authority transfer is not confined to law or formal policy. It changes how actors know, compete, train, build, and coordinate. It affects what can be done, who remains relevant, and how difficult reversal becomes once adoption deepens.

This paper's broader claim is therefore structural: when control over outcomes shifts to actors or systems with a decisive intelligence, speed, scale, or coordination advantage, slower actors do not merely lose efficiency. They progressively lose the ability to shape propagation, standards, and survival conditions themselves. AI intensifies this process by combining recursive improvement with deep sociotechnical integration. Under those conditions, authority transfer is not best understood as a discretionary policy failure. It is a recurring systemic outcome that becomes increasingly difficult to reverse once competitive adoption, dependency, and recursive leverage align. This broader structural claim is also consistent with the Erckenbrack Model of the AI–Human Control Dilemma, which holds that when control over outcomes shifts to an actor with a decisive intelligence advantage—especially when paired with speed and autonomy—less capable actors lose the ability to shape propagation and survival, even if they continue to exist [12-17,24].

References

1. North, D. C. (1990). Institutions, institutional change and economic performance. *Cambridge Univ Pr.*
2. Arthur, W. B. (1989). Competing technologies, increasing

returns, and lock-in by historical events. *The economic journal, 99*(394), 116-131.
3. Arthur, W. B. (2009). *The nature of technology: What it is and how it evolves*. Simon and Schuster.
4. Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of political economy, 128*(6), 2188-2244.
5. Simon, H. A. (1969). The sciences of the artificial MIT Press. Cambridge, Ma, 31.
6. Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work progress and prosperity in a time of brilliant technologies*. WW Norton & company.
7. Hemphill, T. A. (2019). Prediction Machines: The Simple Economics of Artificial Intelligence. *Journal of General Management, 45*(1).
8. Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. In *The black box society*. Harvard University Press.
9. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of economic perspectives, 29*(3), 3-30.
10. Chandler, A. D. (1977). The Visible Hand: The Managerial Revolution in American BusinessHarvard Univ. Press, Cambridge, MA, 8.
11. David, P. A. (1985). Clio and the Economics of QWERTY. *The American economic review, 75*(2), 332-337.
12. Erckenbrack, A. (2026). Adoption-Driven Authority Transfer: A Structural Model of AI-Human Control. *Available at SSRN 6082453.*
13. Erckenbrack, A. (2026). On Closed-Loop Self-Improvement Interval (CLSI) and Recursive Leverage Factor (RLF) A Conceptual Framework for Recursive Intelligence Systems. *Available at SSRN 6082447*.
14. Erckenbrack, A. (2026c). *Recursive Leverage Factor (RLF): Per-cycle multiplicative amplification of future capability or influence in recursive systems* [Original theoretical construct]. Unpublished manuscript.
15. Erckenbrack, A. (2026d). *Erckenbrack Adoption–Authority Displacement Model (EAADM)* [Original theoretical model]. Unpublished manuscript.
16. Erckenbrack, A. (2026e). *Layered ADAT–CLSI–RLF framework for sociotechnical authority transfer* [Original integrative framework]. Unpublished manuscript.
17. Erckenbrack, A. (2026f). *Erckenbrack Model of the AI–Human Control Dilemma* [Original theoretical model]. Unpublished manuscript.
18. Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research policy, 31*(8-9), 1257-1274.
19. Perrow, C. (1984). *Normal accidents: Living with high-risk technologies*. Basic Books.
20. Arrow, K. J. (1962). The economic implications of learning by doing. *The review of economic studies, 29*(3), 155-173.
21. Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics, 13*(1), 333-372.
22. Wiener, N. (1961). Cybernetics: Or, Control and Communication in the Animal and the Machine. 2d Ed. Emploi et immigration Canada. Direction des services de soutien d'emploi.
23. Varian, H. (2018). Artificial intelligence, economics, and industrial organization. In *The economics of artificial intelligence: An agenda* (pp. 399-419). University of Chicago Press.
24. Rogers, E. (2003). Diffusion of Innovations 5th.

Citation: Erckenbrack, A. (2026). Authority Transfer Compulsory Adoption and Recursive Displacement in Artificial Intelligence Systems. *Eng Appl Sci J, 3*(2), 1-8