

Trajectory and Residue

How Work Becomes What Continues to Hold

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Abstract

We formalize a selection-theoretic account of why institutions systematically reward signal management over real work, and propose an alternative infrastructure in which work is evaluated and compensated according to what persists under pressure. Modern institutions optimize for the management of signals rather than the closure of constraints. This produces a stable class of roles—identified by David Graeber as “bullshit jobs” [1]—whose function is not to resolve real-world pressures but to mediate, translate, and amplify representations of work. This document formalizes that diagnosis as a selection problem and proposes an alternative infrastructure in which work is evaluated, routed, and compensated according to persistent constraint closure. The core shift replaces activity-based metrics with trajectory-based residue: evidence that a system resisted, was repaired, and remained stable over time. Three adversarial refinements—causal dependency, distributed attribution, and stress-weighted persistence—are incorporated to ensure the residue function cannot be gamed without genuine interaction with real constraints. The result is a framework for reorganizing labor markets around verifiable interaction with reality rather than credentialed coordination.

1. The Existing Selection Function

Let a system of work allocation be defined by a selection function \mathcal{S} that maps observed signals σ to resource allocation decisions R :

$$\mathcal{S} : \sigma \rightarrow R$$

In current institutional environments, σ consists primarily of activity counts such as tickets, commits, and meetings; credentials including degrees, titles, and affiliations; and narrative coherence in the form of reports, presentations, and alignment language.

These signals are not required to correspond to constraint closure. Instead, they are optimized for legibility to management structures. The resulting equilibrium is characterized by high signal production, low constraint interaction, and stable mediation layers.

This is the formal condition for the persistence of bullshit jobs [1]: roles that maximize σ without engaging the underlying system constraints. When a measure becomes a target, it ceases to be a good measure [2, 3].

Proposition 1. *Under \mathcal{S} , the dominant strategy for an agent seeking to maximize R is to produce high-volume, low-cost signals rather than to close constraints. Since signals are cheaper to produce and more directly legible to \mathcal{S} than constraint closure, agents rationally allocate effort toward signal production [17, 10]. Signal production and constraint closure are therefore decoupled at equilibrium.*

The managerial, credentialing, and recruiter layers that characterize contemporary labor markets are not inefficiencies—they are stable equilibria of \mathcal{S} [4].

2. Constraint Closure as the Primitive

Definition 1 (Constraint). *A constraint is a condition imposed by reality on a system's behavior. A constraint $c \in C$ is closed when the system reaches a state in which c is satisfied and remains satisfied under perturbation.*

Let C be a set of constraints over a system X . A closure event is a transition:

$$X_t \rightarrow X_{t+1} \quad \text{such that} \quad C(X_{t+1}) = 0$$

where $C(\cdot) = 0$ indicates satisfaction.

Instantaneous satisfaction is insufficient. A constraint closed at $t + 1$ may reopen under load, under compositional stress, or as downstream systems evolve. Closure is therefore not a point event but a trajectory-dependent quantity, whose value is determined by what survives subsequent interaction. The operative notion is therefore not satisfaction but *residue*: the durable trace left by a closure event in a system subject to ongoing interaction.

3. Residue: The Basic Definition

Definition 2 (Closure Residue). *Let r be a repair event that closes a constraint c at time t . The closure residue of r over window $[t, t + \Delta]$ is:*

$$\rho(r) = \int_t^{t+\Delta} \mathbb{I}[C(X_\tau) = 0] \cdot D(\tau) \cdot S(\tau) d\tau$$

where $D(\tau)$ is the causal dependency weight at time τ and $S(\tau)$ is the stress intensity at time τ .

Any definition of residue that can be satisfied without interacting with real constraints will be optimized for without producing value. The three terms above are therefore not design choices but adversarial requirements: each must be defined so that gaming it is equivalent to doing the work. The following three sections address them in turn.

4. Causal Dependency

The naive reading of $D(\tau)$ is structural: system B declares that it depends on system A . This is exploitable. Agents can inflate dependency graphs to amplify residue scores without producing causal reliance.

The correct formulation treats dependency as *sensitivity under perturbation*. System B causally depends on closure r if and only if the removal of r increases the probability of failure in B .

Definition 3 (Causal Dependency Weight).

$$D(\tau) = \sum_{j \in \text{downstream}} w_j \cdot \Delta P(\text{failure}_j \mid \neg r, \tau)$$

where $\Delta P(\text{failure}_j \mid \neg r, \tau)$ is the increase in failure probability for downstream system j when the repair r is counterfactually removed at time τ , and w_j is a weight proportional to the criticality of system j .

This formulation aligns the framework with interventionist causality [5, 6]. Dependency is not declared; it is measured by failure propagation. This differs from structural dependency graphs, which encode declared relationships rather than causal sensitivity under intervention. A repair that no downstream system relies on—regardless of how many systems annotate it as a dependency—contributes zero to $D(\tau)$.

Definition 4 (Metric vs. Constraint). *A metric $m : X \rightarrow \mathbb{R}$ is an observation channel. A constraint $c(X, E) = 0$ is a resistance relation whose satisfaction depends on interaction with an environment E that the evaluated agent does not fully control. Metrics can be fabricated by manipulating what the system records. Constraints cannot be fabricated without changing what the system must survive.*

This distinction is load-bearing. Any residue term reducible to a metric controlled by the evaluated agent collapses back into \mathcal{S} .

5. Distributed Attribution

The current draft assumes that a repair r can be associated cleanly with a single agent. In practice, most nontrivial closures are composite: partial fixes, prior groundwork, review interventions, and subsequent stabilizations each contribute to the final residue.

Without explicit handling, the system drifts toward last-touch attribution: the agent who closes the ticket receives full credit, regardless of who performed the diagnostic work, who identified the root cause, or who stabilized the environment that made repair possible. This is easy to exploit.

The correct approach treats each closure event as a directed acyclic graph (DAG) of contributing actions, and assigns credit via a marginal-contribution decomposition analogous to cooperative game attribution [7, 8].

Definition 5 (Marginal Contribution). *Let $\mathcal{A} = \{a_1, \dots, a_n\}$ be the set of actions contributing to closure residue ρ . The marginal contribution of action a_i is:*

$$\rho_i = \mathbb{E}[\rho \mid \text{with } a_i] - \mathbb{E}[\rho \mid \text{without } a_i]$$

This is a Shapley-style decomposition [7] over the repair graph. It is computationally expensive in the general case, but approximate versions operating over observable repair DAGs would substantially improve resistance to gaming. The key property is that credit is *marginal contribution to closure*, not proximity to the final commit or the final ticket resolution.

Agents who perform diagnostic groundwork, stabilize test environments, or review repairs that would otherwise have introduced regressions accumulate residue proportional to their counterfactual impact. Agents who append low-value actions to high-residue repair chains do not.

6. Stress-Weighted Persistence

Duration alone is insufficient as a persistence measure. A trivial fix that is never exercised again will appear persistent simply because nothing has reopened the constraint. What matters is not whether a closure holds over time, but whether it holds *under conditions that would reveal failure*.

Definition 6 (Stress Term). *$S(\tau)$ measures the intensity of system interaction, load, or adversarial conditions at time τ . Operationally, it can be estimated from throughput and request volume, the frequency of adjacent constraint activations, and the presence of concurrent incidents in dependent systems.*

With the stress term incorporated, the residue integral rewards closures that survive load. A repair holding under high $S(\tau)$ accumulates residue rapidly. A repair in a system that has gone dormant accumulates little, regardless of how long it nominally

persists. In software systems, this corresponds to fixes that hold under production traffic rather than only under test conditions.

This prevents dead zones—abandoned subsystems, deprecated codepaths—from generating artificial residue through inactivity.

7. The Refined Residue Function

Assembling the three refinements:

Definition 7 (Refined Closure Residue).

$$\rho(r) = \int_t^{t+\Delta} \mathbb{I}[C(X_\tau) = 0] \cdot \left(\sum_{j \in \text{downstream}} w_j \cdot \Delta P(\text{failure}_j \mid \neg r, \tau) \right) \cdot S(\tau) d\tau$$

with marginal attribution $\rho_i = \mathbb{E}[\rho \mid \text{with } a_i] - \mathbb{E}[\rho \mid \text{without } a_i]$ distributed across the contributing action DAG.

This function has three adversarial properties that follow from its construction. First, dependency must be causal: annotating connections that do not correspond to actual failure propagation does not increase $D(\tau)$. Second, attribution is distributed: last-touch exploitation is suppressed, and marginal contribution over the full repair DAG determines credit allocation. Third, persistence must be exercised: closures accumulate residue only under conditions of real system stress, and dormant fixes do not.

Faking high residue under this function requires actually interacting with real constraints under real load. That is not gaming the system—it is doing the work.

7.1. Exogeneity Condition

A further adversarial pressure is synthetic stress: an agent controls both the intervention and the environment that validates it, generating artificial load to inflate $S(\tau)$. Bot traffic, fake dependencies, synthetic incidents, and self-generated load must therefore be discounted unless they correspond to externally consequential use.

The requirement is that valid stress be causally tied to real downstream reliance, not merely to volume. Define:

Definition 8 (Valid Stress).

$$S_{\text{valid}}(\tau) = S(\tau) \cdot E_{\text{exo}}(\tau) \cdot D(\tau)$$

where $E_{\text{exo}}(\tau) \in [0, 1]$ measures the independence of the stress source from the agent being evaluated. Stress generated or controlled by the evaluated agent is discounted toward zero.

Stress counts only when paired with causal dependency and external consequence. The exogeneity condition prevents an agent from being both the source and the beneficiary of the load that validates their work.

7.2. Maintenance Residue

The repair-event formulation risks a perverse incentive: agents may allow constraints to fail in order to generate repair events and accumulate residue. The fix is to distinguish repair residue from maintenance residue.

Repair residue $\rho_{\text{repair}}(r)$ arises from closing a violated constraint. Maintenance residue arises from keeping a constraint closed under valid stress in the absence of a discrete failure event:

Definition 9 (Maintenance Residue).

$$\rho_{\text{maint}}(a) = \int_t^{t+\Delta} \mathbb{I}[C(X_\tau) = 0] \cdot D(\tau) \cdot S_{\text{valid}}(\tau) \cdot M_a(\tau) d\tau$$

where $M_a(\tau)$ estimates the marginal contribution of agent a 's preventative actions to continued closure at time τ .

Total residue is then:

$$\rho_{\text{total}} = \rho_{\text{repair}} + \rho_{\text{maint}}$$

This rewards the agent whose work makes failure less likely in the first place, not only the agent who resolves failures after they occur.

8. Trajectories Rather Than Snapshots

Let a worker's contribution be modeled as a trajectory through constraint space:

$$\gamma : t \mapsto X_t$$

The value of the trajectory is not the number of interventions but the cumulative residue of closures along it, weighted toward recent persistence under stress:

$$V(\gamma) = \sum_i \rho_i \cdot e^{-\lambda(t-t_i)}$$

where $\lambda > 0$ is a decay parameter. This prevents static reputations from dominating: residue from closures that are no longer stress-tested decays, while active maintenance under load continues to accumulate. This replaces pointwise metrics with path-dependent evaluation.

Two trajectories with equal activity counts can differ dramatically:

Trajectory type	Activity	$V(\gamma)$
High activity, low persistence	High	Low
Low activity, high persistence under stress	Low	High

The current selection function \mathcal{S} cannot distinguish these trajectories. The replacement function \mathcal{S}' can.

9. The Replacement Selection Function

Definition 10 (Residue-Based Selection Function).

$$\mathcal{S}' : \rho(\gamma) \rightarrow R$$

Resources—tasks, compensation, authority—are allocated according to accumulated and recent closure residue, distributed via marginal attribution over contributing action DAGs.

The equilibrium under \mathcal{S}' differs structurally from the equilibrium under \mathcal{S} : only actions that produce persistent, stress-tested, causally integrated closure accumulate value; all other signals are neutral or decaying.

Bullshit jobs—roles that maximize σ under \mathcal{S} —do not satisfy \mathcal{S}' . They are not filtered by gatekeeping; they simply fail to accumulate residue.

The distinction between \mathcal{S} and \mathcal{S}' is not normative but structural: one operates on signals independent of constraint interaction; the other operates on residue produced by it.

10. Economic Routing

Measurement alone is insufficient unless it controls allocation. \mathcal{S}' must route not just evaluation but resources: work opportunities, payment, and decision authority.

Without economic routing, the residue framework becomes a descriptive overlay—a better dashboard for the same managerial layer it is intended to replace.

The mechanism must place resource allocation decisions downstream of $\rho(\gamma)$, bypassing institutional hierarchy.

The near-term viable domain for this is contract and freelance markets where buyers can observe constraint surfaces directly, open systems where incident and dependency graphs are partially public, and environments where the cost of failure is immediate and attributable.

In these domains, buyers can select contributors based on demonstrated closure trajectories without requiring credential intermediaries or HR gatekeeping [11, 12]. The recruiter and credentialing layers do not get reformed; they get bypassed.

11. Structural Resistance

Bullshit jobs persist because they serve real interests. They provide control surfaces for institutional hierarchy. They stabilize internal power structures by converting

uncertain, judgment-dependent work into predictable, legible signals. They give institutions a way to manage headcount without depending on autonomous technical judgment.

A residue-based system therefore does not merely compete technically with existing infrastructure. It competes with existing interests.

Adoption will occur where constraint visibility is high and incident surfaces are observable, where the cost of failure is immediate and cannot be absorbed by mediation, and where mediation layers are already thin.

Adoption will be resisted where signaling is more valuable than outcomes—which describes most large institutional environments.

This is not an argument against building the system. It is a prediction about where it will first take hold and where it will face the most friction.

12. Implementation Sketch

A minimal viable implementation does not attempt full generality. It chooses a domain where the incident surface is observable, the dependency structure is partially inferable, and stress signals exist.

The system requires data ingestion from observable systems including repositories, logs, and incident trackers; construction of incident and dependency graphs; attribution of repairs to contributing action DAGs; temporal tracking of persistence under stress; computation of residue scores via marginal attribution; an interface for querying contributor trajectories; and a mechanism for routing tasks and payment based on accumulated residue.

The validation criterion is discriminative power under equal activity: given two contributors with similar activity levels, does the residue-based metric separate them in a way that aligns with expert judgment? If that holds even weakly, the architecture becomes economically interesting and the selection-function argument moves from structural to demonstrable.

13. Evaluation Without a Constraint Surface

The framework developed above applies directly to labor markets, where constraint surfaces are partially observable and residue can be approximated from incident and dependency data. But the same selection-theoretic logic applies wherever evaluation has become decoupled from the underlying structure it once tracked.

Consider a system in which agents historically accumulated residue through repeated interaction with stable constraint sets embedded in social roles. The role provided the

trajectory; the community provided the measurement; observable success and failure under stress provided the residue. Evaluation vocabulary—the words a system uses to distinguish trajectories—was compressed residue: lossy encodings of long-run closure patterns that allowed agents to communicate about trajectory differences without enumerating them.

When the institutional structures that exposed those constraint sets dissolve, the collapse is structural and forced. If trajectories cannot be evaluated against a shared constraint surface, then residue cannot be accumulated or compared. If residue cannot be accumulated or compared, evaluation vocabulary ceases to map to observable distinctions. When vocabulary ceases to map to observable distinctions, it decays. Evaluation then defaults to signals that remain legible under \mathcal{S} : appearance, affiliation, stated identity.

This is not primarily a cultural or emotional phenomenon. It is a measurement collapse: the system can no longer distinguish trajectories that differ in constraint closure, because the constraint surface is no longer exposed.

14. Resentment as Equilibrium Behavior

Under \mathcal{S} , agents who cannot produce high residue but are still ranked by visible signals face a structural problem with no internal solution. Under \mathcal{S} without access to observable ρ , no strategy based on deeper constraint interaction yields higher expected R . The only remaining degrees of freedom are in the interpretation and production of σ .

The dominant response is therefore not to interact more deeply with constraints—that path is closed—but to revalue the ranking system itself:

$$\text{inaccessible } \rho \Rightarrow \text{evaluation collapse} \Rightarrow \text{signal inversion}$$

This is the structural mechanism behind what is sometimes described as resentment or transvaluation [16]: not primarily an emotional state, but the optimal adaptation to operating under \mathcal{S} without access to \mathcal{S}' .

The behavior is stable as long as the measurement layer remains collapsed. Reintroducing observable constraint surfaces—roles, systems, environments where closure is visible and stress-testable—changes the equilibrium without requiring any change in the agents themselves. The problem is not the agents. The problem is the missing measurement layer.

15. Role Dissolution as Trajectory Collapse

Historically, stable social roles functioned as constrained trajectory spaces. A role instantiated a persistent mapping γ under a fixed constraint set C , with publicly observable closure and failure events. The role was not merely a job description—it was a scaffold for accumulating residue in a shared measurement system. Evaluation vocabulary was calibrated against that accumulation.

When roles dissolve, the shared constraint set C and the observability of closure events are removed simultaneously, eliminating the possibility of shared residue accumulation. Agents are left in unconstrained space with no stable external basis for evaluation. The vocabulary that once described trajectory differences becomes decorative rather than functional, because the underlying structures it referred to are no longer exposed.

The repair is not to restore the old roles. It is to restore exposure to constraint surfaces: environments where systems resist, repairs are visible, and closures persist under stress. The vocabulary re-emerges after the measurement system is restored, not before.

This is a direct extension of \mathcal{S}' beyond labor markets. The replacement selection function does not require shared tradition, inherited language, or institutional continuity. It requires only that constraint surfaces be observable, that closures be attributable, and that residue accumulate in proportion to genuine interaction with reality.

16. Dynamic Constraint Fields

The preceding formulation treats constraints as discrete conditions evaluated over system states. In practice, constraints evolve as functions of both system configuration and environmental interaction. We therefore refine the model by treating constraints as a field over state space.

Let the system be defined over a domain Ω with state $X : \Omega \times \mathbb{R} \rightarrow \mathcal{X}$. A constraint field is a mapping

$$\mathcal{C} : \mathcal{X} \times \mathcal{E} \rightarrow \mathbb{R}^k$$

such that $\mathcal{C}(X, E) = 0$ defines the manifold of satisfied constraints.

Closure is no longer a pointwise event but a trajectory that remains within the zero-set of \mathcal{C} under system evolution:

$$\forall \tau \in [t, t + \Delta], \quad \mathcal{C}(X_\tau, E_\tau) = 0.$$

This formulation allows constraints to shift, tighten, or couple over time [21]. Residue therefore measures not only persistence but stability under a moving constraint surface. The residue integral remains well-defined under this generalization, with the indicator function replaced by membership in the constraint manifold.

17. Adversarial Behavior and Gaming Resistance

Any selection function that allocates resources induces strategic behavior. A valid framework must therefore be evaluated not only under honest participation but under adversarial optimization.

Let an agent choose actions $a \in \mathcal{A}$ to maximize expected reward under \mathcal{S}' . A gaming strategy is any policy π that increases $\mathbb{E}[V(\gamma)]$ without increasing true constraint closure.

The primary attack vectors are as follows.

Synthetic Dependency Inflation. Agents construct artificial dependency graphs to increase $D(\tau)$. This is neutralized by counterfactual dependency measurement: non-causal edges contribute zero.

Stress Fabrication. Agents generate load to increase $S(\tau)$. This is neutralized by the exogeneity filter $E_{\text{exo}}(\tau)$, which discounts self-generated stress.

Attribution Capture. Agents position themselves at terminal points of repair chains to capture credit. This is neutralized by marginal contribution over the repair DAG.

Proposition 2. *Under \mathcal{S}' , any strategy that increases expected reward must increase expected interaction with exogenous constraint surfaces under stress.*

Sketch. Each multiplicative term in ρ is independently grounded in counterfactual or exogenous measurement. Artificial inflation of any single term is nullified unless it produces corresponding changes in failure propagation or externally induced stress. Therefore, increasing ρ requires genuine causal contribution to constraint closure. \square

18. Equilibrium Analysis

We compare the equilibria induced by \mathcal{S} and \mathcal{S}' in a simplified agent model [9, 18].

Let agents choose between two action classes: signal production a_σ and constraint interaction a_c . Let costs satisfy $C_\sigma \ll C_c$, and let rewards depend on the selection function.

Under \mathcal{S} :

$$R_\sigma \gg R_c,$$

since signals are directly observed and rewarded.

Under \mathcal{S}' :

$$R_\sigma \approx 0, \quad R_c \propto \rho.$$

Proposition 3. *The Nash equilibrium under \mathcal{S} is dominated by signal production. The Nash equilibrium under \mathcal{S}' is dominated by constraint interaction.*

Sketch. Under \mathcal{S} , the payoff-to-cost ratio of a_σ exceeds that of a_c , so all agents shift toward signal production. Under \mathcal{S}' , a_σ yields negligible reward, while a_c produces residue proportional to constraint closure. The payoff dominance reverses, and agents converge to constraint interaction. \square

The transition from \mathcal{S} to \mathcal{S}' therefore induces a phase shift in agent behavior, not a marginal adjustment.

19. Information-Theoretic Interpretation

Residue can be interpreted as a measure of irreversible information imprinted into a system through constraint interaction [13, 14, 15].

Let $H(X)$ denote the entropy of system state X . A closure event that stabilizes a constraint reduces the accessible state space of the system. Under repeated stress, this reduction becomes persistent.

Definition 11 (Informational Residue).

$$\rho_{\text{info}}(r) = \int_t^{t+\Delta} \Delta H_{\text{irreversible}}(\tau) \cdot D(\tau) \cdot S_{\text{valid}}(\tau) d\tau$$

where $\Delta H_{\text{irreversible}}(\tau)$ is the irreversible reduction in system entropy induced by the closure at time τ .

This formulation connects residue to thermodynamic work [22, 14]. A closure that does not persist corresponds to reversible fluctuation and leaves no lasting informational trace. Only closures that reduce entropy under stress contribute to residue.

This interpretation clarifies why signal production fails to substitute for constraint interaction: signals can be generated without altering the entropy structure of the underlying system.

20. Interface and Observability

The effectiveness of \mathcal{S}' depends on the observability of constraint interaction. Let \mathcal{O} be the observation operator mapping system dynamics to measurable data:

$$\mathcal{O} : (X_t, E_t) \rightarrow \text{logs, traces, events.}$$

A necessary condition for implementing \mathcal{S}' is that \mathcal{O} captures constraint activation and resolution events, failure propagation across system components [19, 20], stress signals independent of agent control, and temporal persistence under load.

Incomplete observability introduces bias into ρ but does not revert the system to signal-based selection. Instead, it degrades measurement resolution. The design problem is therefore not to eliminate measurement error but to ensure that errors are orthogonal to strategic manipulation. As long as measurement noise is not controllable by agents, the adversarial properties of \mathcal{S}' are preserved.

21. Conclusion

Graeber [1] identified a class of roles that optimize for signal management rather than real work. Their persistence is not accidental. It is the stable equilibrium of a selection function \mathcal{S} that rewards legibility over constraint interaction.

Replacing that function requires three moves: redefining work in terms of trajectory and residue; constructing measurement systems that capture causal dependency, distributed attribution, and stress-weighted persistence; and routing economic decisions through those measurements rather than through credential and title hierarchy.

The goal is not to eliminate coordination. Coordination that closes constraints accumulates residue. The goal is to subordinate coordination to constraint closure, so that roles which exist only to manage representations of work can no longer satisfy the selection function that allocates resources.

The next step is a toy model: agents choosing between signal production and constraint interaction under \mathcal{S} and \mathcal{S}' , with equilibria computed explicitly for each. That model would make the argument not just structural but demonstrable.

Work becomes not what is reported, but what continues to hold.

References

- [1] D. Graeber, *Bullshit Jobs: A Theory*. Simon & Schuster, 2018.
- [2] C. A. E. Goodhart, “Problems of Monetary Management: The U.K. Experience,” in *Papers in Monetary Economics*, Reserve Bank of Australia, 1975.
- [3] M. Strathern, “Improving Ratings: Audit in the British University System,” *European Review*, vol. 5, no. 3, pp. 305–321, 1997.
- [4] R. E. Lucas, “Econometric Policy Evaluation: A Critique,” *Carnegie-Rochester Conference Series on Public Policy*, 1976.
- [5] J. Pearl, *Causality: Models, Reasoning, and Inference*, 2nd ed. Cambridge University Press, 2009.

- [6] P. Spirtes, C. Glymour, and R. Scheines, *Causation, Prediction, and Search*. MIT Press, 2000.
- [7] L. S. Shapley, “A Value for n -Person Games,” in *Contributions to the Theory of Games II*, Princeton University Press, 1953.
- [8] T. Roughgarden, *Twenty Lectures on Algorithmic Game Theory*. Cambridge University Press, 2016.
- [9] M. J. Osborne and A. Rubinstein, *A Course in Game Theory*. MIT Press, 1994.
- [10] K. J. Arrow, *Essays in the Theory of Risk-Bearing*. North-Holland, 1970.
- [11] R. H. Coase, “The Nature of the Firm,” *Economica*, vol. 4, no. 16, pp. 386–405, 1937.
- [12] O. E. Williamson, *The Economic Institutions of Capitalism*. Free Press, 1985.
- [13] R. Landauer, “Irreversibility and Heat Generation in the Computing Process,” *IBM Journal of Research and Development*, vol. 5, no. 3, 1961.
- [14] C. H. Bennett, “The Thermodynamics of Computation—A Review,” *International Journal of Theoretical Physics*, 1982.
- [15] S. Lloyd, “Ultimate Physical Limits to Computation,” *Nature*, vol. 406, pp. 1047–1054, 2000.
- [16] D. Kahneman and A. Tversky, “Prospect Theory: An Analysis of Decision under Risk,” *Econometrica*, vol. 47, no. 2, 1979.
- [17] H. A. Simon, “A Behavioral Model of Rational Choice,” *Quarterly Journal of Economics*, 1955.
- [18] R. J. Aumann, “Subjectivity and Correlation in Randomized Strategies,” *Journal of Mathematical Economics*, 1974.
- [19] A.-L. Barabási and R. Albert, “Emergence of Scaling in Random Networks,” *Science*, 1999.
- [20] M. E. J. Newman, *Networks: An Introduction*. Oxford University Press, 2010.
- [21] S. A. Kauffman, *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford University Press, 1993.
- [22] N. Georgescu-Roegen, *The Entropy Law and the Economic Process*. Harvard University Press, 1971.