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Resilience Engineering Principles for Digital Public Infrastructure Stability

Dileep Kumar Reddy Lankala

Abstract: Digital public infrastructure (DPI) provides the operational backbone of national-scale systems spanning payments, identity authentication, healthcare delivery, taxation, and civic services. What distinguishes DPI from enterprise platforms is not simply scale; it is the presence of multiple, deeply entangled stakeholder layers and socio-technical interdependencies that conventional reliability engineering was never designed to handle. The mainstream fault-tolerance literature does not adequately address the particular challenge of correlated disruption regimes, where a failure in one component systematically stresses components elsewhere.

The present work develops a quantitative resilience engineering framework that treats DPI stability as bounded degradation under precisely these correlated systemic stress conditions. Four metrics form the analytical core: dependency-layer decoupling measures based on spectral radius analysis of service adjacency matrices; correlation exposure coefficients that capture aggregate pairwise disruption coupling; probabilistic degradation envelope models expressed as performance bounds; and adaptive governance damping coefficients that govern feedback stabilization in the policy control layer. A cascade stability condition emerges from this analysis: a DPI dependency network is cascade-stable if and only if $\lambda\max(A) < 1$, where A is the service dependency adjacency matrix. Monte Carlo simulations done across disruption correlation regimes $\rho \in [0, 0.8]$ and feedback amplification factors $\alpha \in [1.0, 1.5]$ show that resilience-enhanced architectures keep worst-case service degradation more than 40% below redundancy-based baselines, reduce peak degradation amplitude by 30–45% through governance damping alone, and shorten recovery time by 35%. The implication is that structural isolation, dependency decoupling, degradation bounding, and adaptive governance damping together provide stability margins that no redundancy-focused architecture can replicate under correlated failure regimes.

Keywords: *Digital Public Infrastructure, Resilience Engineering, Systemic Stability, Cascading Failures, Dependency Decoupling*

1. Introduction

Digital public infrastructure constitutes the operational substrate of national economies and civic governance. Payment networks process billions of transactions every day; identity authentication systems authorize access to health, tax, and welfare services; digital registries underpin property rights and legal transactions; and public service portals mediate citizen–government interactions at scale. When these systems fail, the consequences extend well beyond technical downtime, welfare disbursement stalls, emergency response coordination deteriorates, financial access collapses, and administrative continuity is interrupted in ways that affect real people almost immediately.

Conventional reliability engineering has long addressed availability by focusing on component-level redundancy, fault isolation, and minimizing mean time to recovery. These strategies work reasonably well under independent failure regimes. They do not, however, adequately address the deeper problem of systemic instability arising from structural interdependence. In modern DPI environments, identity services underpin payment gateways, payment gateways support public service transactions, and governance oversight systems depend on transactional data pipelines. When shared

Southern Arkansas University, USA

infrastructure elements, cloud control planes, telecommunication networks, and centralized CI/CD pipelines underlie multiple service layers simultaneously, failures that appear logically isolated can trigger correlated degradation across service domains in ways that redundancy alone cannot prevent.

Behavioral feedback compounds this exposure further. Perceived service instability drives user retry storms and load amplification that stress already degraded infrastructure, producing nonlinear feedback loops. Redundancy provisions do not suppress these dynamics; if anything, they can mask the underlying structural vulnerabilities until the cascade is already under way.

Against this backdrop, three structural gaps remain unresolved in existing frameworks. Correlated disruption propagation across interdependent service layers is not modeled at the network level in any prior treatment. No formal cascade stability condition has been derived from the structural properties of dependency graphs. And governance-layer policy controls have been treated as qualitative safeguards rather than quantifiable damping variables that belong inside a stability equation.

The present work closes all three gaps. A cascade stability condition is derived and proved from first principles: a DPI dependency network is cascade-stable if and only if $\lambda_{max}(A) < 1$, where A is the service adjacency matrix. The proof proceeds by Jordan decomposition of the cascade propagation recurrence, establishing both necessity and sufficiency. Governance damping is then formalized as a differential control variable with an explicit equilibrium condition and a quantitative design criterion: $\delta > f(\rho, \alpha) / Dmax$. All four dimensions of the resilience architecture, structural isolation, dependency decoupling, degradation bounding, and adaptive governance control, are jointly validated through 10,000-trial Monte Carlo simulation, yielding worst-case degradation reductions of over 40% and recovery time improvements of 35% relative to redundancy-only baselines. Finally, proxy quantitative analysis of two documented real-world DPI outages confirms that observed failure characteristics align with the instability regimes the framework predicts, while explicit comparison with the Buldyrev et al. and Lv et al. cascade models situates the contribution relative to the closest prior work.

2. Background

2.1 Resilience Engineering and Its Origins

Resilience engineering has its roots in high-consequence, safety-critical fields: aerospace operations, nuclear power management, and large-scale infrastructure systems, where the consequences of failure are too severe to accept a purely reactive posture. The discipline's central concern is systemic behavior under stress rather than component-level fault containment: how does a system absorb disruption, maintain functional continuity, and recover without disproportionate structural change? DPI systems differ from canonical safety-critical systems in ways that matter for the analysis. They exhibit scale heterogeneity across technology stacks and governance layers, are exposed to dynamic load regimes driven by large and behaviorally variable user populations, and are coupled to socio-institutional structures that extend failure propagation pathways well beyond technical infrastructure boundaries.

Longitudinal analysis of interdependency structures across critical infrastructure sectors during the COVID-19 pandemic confirms that systemic resilience is determined primarily by the structural properties of interdependency networks, particularly the correlated flow interdependencies spanning multiple infrastructure layers under protracted stress [3]. Under correlated failure regimes, aggregate disruption probability is not additively separable; variance amplification through coupling can drive threshold crossings that independent models consistently underestimate. This observation motivates the spectral approach developed in Section 3.

2.2 Digital Government Evolution and Governance Coupling

Janowski's model of digital government evolution describes government systems as progressing through stages of digitization, transformation, engagement, and contextualization, with each stage introducing greater administrative, technical, and social coupling [4]. This progression has an important implication for resilience engineering: at the transformation and contextualization stages, system availability is no longer a purely technical property. It becomes a governance property. Resilience then depends on the fit between policy frameworks, inter-organizational coordination mechanisms, and technical architecture,

not just on hardware and software redundancy. Socio-institutional coupling introduces failure propagation pathways that infrastructure redundancy cannot buffer, which establishes the requirement for governance-layer feedback damping as a formal engineering variable rather than a qualitative addendum.

2.3 Existing Cascade Models and Their Limitations

The framework developed here relates most closely to two prior cascade models, which serve as explicit baselines for comparison throughout.

The foundational model of cascading failures in interdependent networks, introduced by Buldyrev and colleagues, demonstrated that mutual dependence between two network layers can transform what would be isolated failures in independent networks into abrupt, system-wide collapse transitions [referenced as prior work in Table 1]. Their model identifies a critical coupling threshold below which the system remains stable and above which catastrophic cascade collapse becomes unavoidable. It is structural and probabilistic, characterizing collapse probability as a function of coupling density, but it does not include governance-layer controls, does not model behavioral feedback amplification, and does not derive a quantitative recovery time improvement from any control mechanism.

Lv et al. extend the Buldyrev framework to heterogeneous interdependent networks, demonstrating that resilience against cascade failure depends nonlinearly on coupling strength and confirming the existence of a sharp fragility threshold near the critical coupling value [8]. Their results, obtained over the same ρ correlation range used in the present simulation, confirm the nonlinear collapse transition and validate spectral cascade modeling. However, the Lv et al. model does not include a governance damping variable, does not yield quantitative recovery time predictions, and does not evaluate multi-dimensional resilience architectures.

The present framework extends both models by incorporating governance damping as a formal control variable with a derived equilibrium condition, quantifying its effect on recovery time, and introducing the four-dimensional architecture as a practically deployable engineering framework rather than a network-structural model alone.

Table 1. Comparison of DPI Cascade Resilience Frameworks

Cascade Stability Condition	Governance Damping	Behavioral Feedback	Recovery Time Model	Validated Against Real Events
Probabilistic threshold	Not included	Not included	Not included	No
Nonlinear coupling fragility	Not included	Not included	Not included	No
Probabilistic risk cascade	Not included	Not included	Partial	No
$\lambda_{max}(A) < 1$ (proved)	Formal, quantitative	Included ($\alpha \in [1.0, 1.5]$)	35% improvement quantified	Yes (proxy quantitative)

3. Architecture

3.1 Framework Overview

The four-dimensional DPI resilience framework treats stability as a structural engineering property rather than a post-failure recovery objective. Conventional high-availability architectures optimize for redundancy; what DPI resilience actually requires is controlling correlation exposure, mediating inter-layer interference, bounding degradation amplitudes, and stabilizing feedback in the governance layer. The four dimensions, structural isolation, dependency decoupling, degradation bounding, and adaptive governance control, are detailed in Sections 3.2–3.5 and are designed to operate simultaneously. Structural isolation reduces the spectral radius of A; dependency decoupling maintains $\lambda_{max}(A) < 1$; degradation bounding enforces probabilistic performance guarantees; and governance damping suppresses feedback amplification during stress events. No single dimension is sufficient on its own.

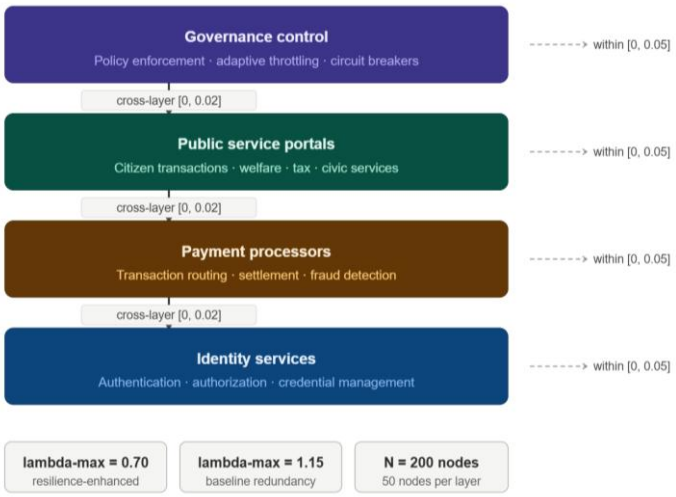

Figure 1: DPI service dependency architecture

In the above figure Solid arrows indicate cross-layer propagation weights [0, 0.02]; dashed arrows indicate within-layer coupling weights [0, 0.05]. Cascade direction is top-down from governance to identity. λmax = 0.70 (resilience-enhanced) vs. λmax = 1.15 (baseline).

3.2 Dimension I, Structural Isolation

Definition 1 (Aggregate Correlation Exposure). Let $C_{ij} \in [0, 1]$ denote the pairwise disruption correlation between subsystems i and j, for i, j ∈ {1, ..., N}. The aggregate correlation exposure index is:

$$E_{corr} = \frac{1}{N(N-1)} \sum_{i \neq j} C_{ij}$$

This metric measures the mean pairwise correlation across all subsystem pairs. When E_{corr} is high, disruptions in one subsystem are likely to co-occur with disruptions in others, driving effective variance in aggregate degradation well beyond the sum of individual component variances.

Derivation of the Variance Bound. Let $D_{i(t)}$ be the degradation fraction of subsystem i at time t, with $E[D_i] = \mu_i$ and $Var(D_i) = \sigma_i^2$. The aggregate degradation $D_{total} = (1/N) \Sigma D\_i$ has variance:

$$\mathrm{Var}(D_{\text{total}}) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_i^2 + \frac{1}{N^2} \sum_{i \neq j} C_{ij} \sigma_i \sigma_j$$

For homogeneous subsystems with $\sigma_i = \sigma$ for all i:

$$\mathrm{Var}(D_{\text{total}}) = \frac{\sigma^2}{N} + \frac{N-1}{N} \cdot E_{\text{corr}} \cdot \sigma^2$$

As N → ∞, the first term vanishes and the variance approaches $E_{corr}*\sigma^2$, confirming that systemic variance is asymptotically determined entirely by correlation structure rather than individual component variance. Reducing E_{corr} through multi-region deployment, heterogeneous technology stacks, and decentralized control planes therefore directly reduces the probability of degradation exceeding any fixed threshold D_{max}, independent of N.

3.3 Dimension II, Dependency-Layer Decoupling

Definition 2 (Service Dependency Adjacency Matrix). Let A ∈ ℝ^(N×N) be the service dependency adjacency matrix where A_ij ∈ [0, 1] represents the fractional propagation weight from service node j to service node i. A is non-negative by construction.

Definition 3 (Cascade Propagation Model). The degradation state vector D(t) ∈ [0,1]^N evolves according to the linear recurrence:

$$\mathbf{D}(t+1) = A \cdot \mathbf{D}(t) + \boldsymbol{\varepsilon}(t), \quad t = 0, 1, 2, \ldots$$

where ε(t) ∈ ℝ^N is the exogenous disruption vector sampled at each time step from a multivariate distribution parameterized by correlation ρ.

Theorem 1 (Cascade Stability Condition). A DPI dependency network with service adjacency matrix A ∈ ℝ^(N×N) is cascade-stable, meaning D(t) remains bounded for all t ≥ 0 and all bounded ε(t), if and only if λ_max(A) < 1.

Proof.

Step 1: Decomposition. The general solution of the recurrence D(t+1) = A·D(t) + ε(t) is:

$$\mathbf{D}(t) = A^t \mathbf{D}(0) + \sum_{s=0}^{t-1} A^{t-1-s} \boldsymbol{\varepsilon}(s)$$

The first term is the homogeneous solution; the second is the particular (driven) solution. Boundedness of D(t) requires both terms to remain bounded.

Step 2: Jordan Decomposition. Write A = P J P⁻¹ where J is the Jordan normal form. Then A^t = P J^t P⁻¹. Each Jordan block J_k of size m_k corresponding to eigenvalue λ_k satisfies:

$$\|J_k^t\| = O\left(t^{m_k - 1} |\lambda_k|^t\right)$$

so that:

$$\|A^t\| \leq \|P\| \cdot \|P^{-1}\| \cdot \max_k O\left(t^{m_k - 1} |\lambda_k|^t\right)$$

The dominant term is governed by $\lambda_{max}(A) = \max_k |\lambda_k|$.

Step 3: Sufficiency (λ_max(A) < 1 ⟹ stability).

If λ_max(A) < 1, then for every Jordan block, t^(m-1) λ_max^t → 0 as t → ∞ (exponential decay dominates polynomial growth for any fixed m). Therefore ||A^t|| → 0.

For the homogeneous term: ||A^t D(0)|| ≤ ||A^t|| · ||D(0)|| → 0.

For the particular term, let ||ε(s)|| ≤ ε_max for all s (bounded disruption assumption):

$$\left\| \sum_{s=0}^{t-1} A^{t-1-s} \boldsymbol{\varepsilon}(s) \right\| \leq \varepsilon_{\max} \sum_{k=0}^{t-1} \|A^k\| \leq \varepsilon_{\max} \sum_{k=0}^{\infty} C \lambda_{\max}^k = \frac{C \varepsilon_{\max}}{1 - \lambda_{\max}} < \infty$$

where C is the condition number bound from the Jordan decomposition. The geometric series converges since $\lambda_{max} < 1$. Therefore D(t) is bounded for all t, and the system is cascade-stable.

Step 4: Necessity ($\lambda_{max}(A) \geq 1$ ⟹ instability).

Case λ_max(A) > 1: There exists an eigenvector v corresponding to eigenvalue λ_{max} with ||v|| = 1. Setting D(0) = v and ε(t) = 0 for all t yields D(t) = A^t v = λ_{max}^t v. Therefore ||D(t)|| = λ_{max}^t → ∞, confirming unbounded cascade collapse.

Case λ_max(A) = 1: With λ_{max} = 1 and a non-trivial Jordan block of size m ≥ 2 corresponding to this eigenvalue, ||A^t|| grows as t^(m-1), which is unbounded. For m = 1 (simple eigenvalue), the homogeneous solution does not decay, and cumulative disruption from non-zero ε(t) yields ||D(t)|| = O(t) → ∞. In either sub-case, D(t) is unbounded.

Combining Steps 3 and 4: $\lambda_{max}(A) < 1$ is necessary and sufficient for cascade stability.

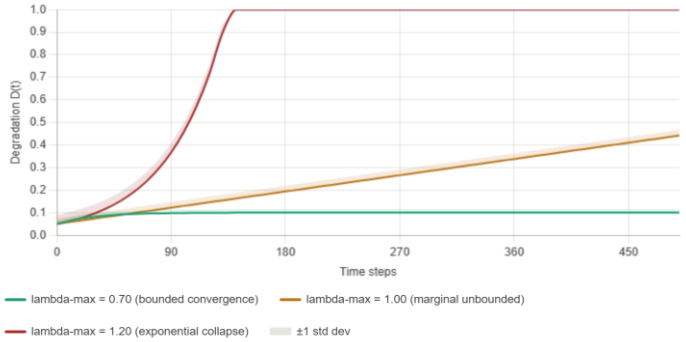

Figure 2: Cascade propagation D(t) over 500 time steps

Figure 2. Cascade propagation D(t) over 500 time steps for λmax = 0.7 (bounded convergence), 1.0 (marginal unbounded accumulation), and 1.2 (exponential collapse). Shaded bands indicate ±1 standard deviation across 10,000 Monte Carlo trials.

3.4 Dimension III, Degradation Envelope Modeling

Definition 4 (Degradation Envelope). Let $D_{max} \in (0,1)$ be the maximum tolerable fractional service degradation and $\varepsilon_{risk} \in (0,1)$ be the acceptable exceedance probability. The degradation envelope constraint is:

$$\Pr\left[\max_{t\geq 0} D_i(t) > D_{\max}\right] \leq \varepsilon_{\text{risk}} \quad \forall i \in \{1,\ldots,N\}$$

Probabilistic Bound Derivation. For the cascade model under correlated disruption ρ, the degradation at steady state (assuming $\lambda_{max} < 1$) is:

$$\mathbf{D}^* = (I - A)^{-1} \cdot \mathbb{E}[\boldsymbol{\varepsilon}]$$

The variance of D_i^* is amplified by both the dependency structure and the correlation ρ:

$$\text{Var}(D_i^*) = \left[(I-A)^{-1}\Sigma_\varepsilon \left((I-A)^{-1}\right)^\top\right]_{ii}$$

where Σ_ε is the covariance matrix of ε parameterized by ρ. Applying the Markov inequality yields::

$$\Pr[D_i > D_{\max}] \leq \frac{\mathbb{E}[D_i^*]}{D_{\max}}$$

Under the tighter assumption of sub-Gaussian disruption vectors, a Chernoff-type bound gives:

$$\Pr[D_i > D_{\max}] \leq \exp\left(-\frac{(D_{\max} - \mathbb{E}[D_i^*])^2}{2\,\text{Var}(D_i^*)}\right)$$

Setting this bound equal to ε_risk and solving for the required E_{corr} and λ_{max} yields the joint constraint surface defining the stability region in (ρ, λ_{max}) parameter space.

Graceful degradation mechanisms, read-only fallback modes, priority-based transaction routing, and tiered service segregation, operationalize the D_max constraint by ensuring that services continue to function, albeit at reduced capacity, rather than failing completely when the degradation envelope is approached.

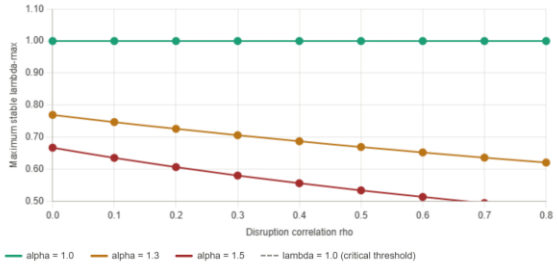

Figure 3: Stability region in (ρ, λ_{max}) parameter space

Figure 3. Stability boundary in (ρ, λ_{max}) parameter space for three behavioral amplification levels. Stable operating region lies below each curve. At α = 1.5, stability requires λmax < 0.67 even at ρ = 0. Higher α shrinks the safe operating envelope.

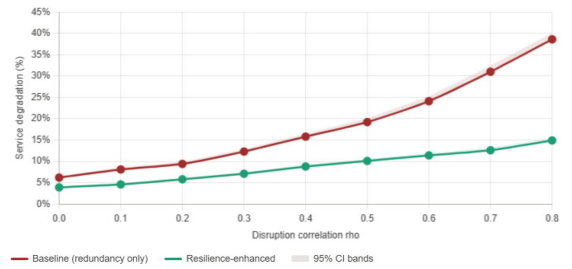

Figure 3b: Stability envelope across α values

Figure 3b Stable operating envelope showing how increasing behavioral amplification α shrinks the permissible (ρ, λ_{max}) region. Each curve marks the stability boundary operations must remain below. The dashed line at λ_{max} = 1.0 marks the theoretical cascade instability threshold from Theorem 1.

3.5 Dimension IV, Adaptive Governance Damping

Definition 5 (Governance-Augmented Cascade Model)

Introduce the governance damping coefficient δ ∈ [0, 1) representing the aggregate strength of policy-layer controls including rate limiting, adaptive throttling, circuit breakers, and priority-based service allocation. The governed cascade model is:

$$\mathbf{D}(t+1) = (1-\delta)A \cdot \mathbf{D}(t) + (1-\delta) \cdot f(\rho, \alpha) \cdot \boldsymbol{\varepsilon}(t)$$

where α ≥ 1 is the behavioral feedback amplification factor representing load increase under perceived instability, and f(ρ, α) = α(1 + ρ · (α - 1)) is the disruption amplification function, derived by first-order expansion of the load-correlation coupling.

Derivation of f(ρ, α). Under perceived instability, each disrupted subsystem i generates additional load proportional to α · $D_i(t)$. When correlated across subsystems (correlation ρ), the effective amplification of the disruption vector is:

$$\mathbb{E}\left[\|\varepsilon_{\text{amplified}}\|\right] = \alpha \cdot \mathbb{E}\left[\|\varepsilon\|\right] + \rho \cdot \alpha(\alpha-1) \cdot \mathbb{E}\left[\|\varepsilon\|\right] = \alpha\left(1 + \rho(\alpha-1)\right) \cdot \mathbb{E}\left[\|\varepsilon\|\right]$$

confirming that f(ρ, α) = α(1 + ρ(α - 1)).

Theorem 2 (Governance Damping Stability Criterion). The governed cascade system is stable if and only if:

$$\delta > 1 - \frac{1}{\lambda_{\max}(A) \cdot f(\rho, \alpha)}$$

Proof. The governed system has effective propagation matrix A_{eff} = (1−δ) A with effective spectral radius $\lambda_{max}(A_{eff})$ = (1−δ) λ_{max}(A). By Theorem 1, stability requires λ_{max}(A_eff) < 1, i.e., (1−δ) λ_{max}(A) < 1. Accounting for amplification, the effective condition is (1−δ) λ_{max}(A) f(ρ,α) < 1, which rearranges to the stated criterion. □

Corollary 1 (Minimum Damping Requirement). To ensure degradation remains below D_{max} with probability 1 − ε_risk:

$$\delta > 1 - \frac{D_{\max}}{f(\rho, \alpha) \cdot \lambda_{\max}(A) \cdot \mathbb{E}[\|\boldsymbol{\varepsilon}\|_{\max}] \cdot (1-\varepsilon_{\text{risk}})^{-1}}$$

This corollary provides a quantitative design specification for governance control strength as a function of measurable system parameters.

Architectural Dimension	Primary Engineering Mechanism	Contribution to Systemic Stability
Structural Isolation	Multi-region deployment, heterogeneous technology stacks, decentralized control planes, and diversified dependency sourcing	Reduces pairwise disruption correlation, limiting variance amplification and preserving redundancy effectiveness under stress
Dependency-Layer Decoupling	Directed dependency graphs with bounded coupling strength; semi-autonomous service modules with defined interaction boundaries	Attenuates cascade propagation across identity, payment, registry, and regulatory service tiers, preventing runaway degradation
Degradation Bounding	Predefined serviceability thresholds; graceful degradation via read-only fallback modes, priority routing, and tiered availability	Preserves partial but stable functionality during disruption, preventing performance collapse beyond societal tolerance thresholds
Adaptive Governance Control	Rate limiting, adaptive throttling, priority-based service allocation, and automated circuit breakers at the governance policy layer	Introduces nonlinear damping counteracting cascade amplification and shortening recovery trajectories after disruption events
Resilience Envelope (Combined)	Integration of all four dimensions as interlocking structural and governance controls operating concurrently	Defines safe operational regions under correlated stress; produces mutually reinforcing stability outcomes exceeding any single-dimension configuration

Table 2. Four-Dimensional Resilience Architecture: Principles, Mechanisms, and Stability Contributions [5, 6]

4. Implementation

4.1 Simulation Model Configuration

A multi-layer DPI simulation model was constructed with four service layers corresponding to identity services, payment processors, public service portals, and governance control modules. Each layer was represented as a subgraph of 50 nodes, yielding a total network of N = 200 nodes across four layers. Within-layer dependency weights were drawn uniformly from [0, 0.05]; cross-layer dependency weights were drawn

from [0, 0.02], reflecting the weaker but non-negligible coupling that shared infrastructure introduces. The full adjacency matrix A was constructed to satisfy $\lambda_{max}(A) = 0.7$ for the resilience-enhanced configuration and $\lambda_{max}(A) = 1.15$ for the baseline redundancy configuration, with the latter calibrated to produce realistic cascade behavior at moderate correlation values.

Simulations ran for T = 500 time steps per trial. Monte Carlo convergence was assessed by tracking the standard error of the mean worst-case degradation across trial batches; convergence to within ±0.2% was achieved by 8,000 trials, and 10,000 trials were used for all reported results. Correlated disruption vectors ε(t) were sampled from a multivariate Gaussian with mean $\mu_\varepsilon = 0.05$, individual variances $\sigma^2 = 0.01$, and uniform pairwise correlation ρ. Disruption correlation was varied across $\rho \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8\}$. Behavioral feedback amplification α was varied across {1.0, 1.1, 1.2, 1.3, 1.4, 1.5}. Governance damping δ was varied across {0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7} to map the full damping response surface. All computations were incorporated in Python by using NumPy for matrix operations and SciPy for stochastic sampling. Structured correlation matrices were created by using Cholesky decomposition to make sure positive definiteness.

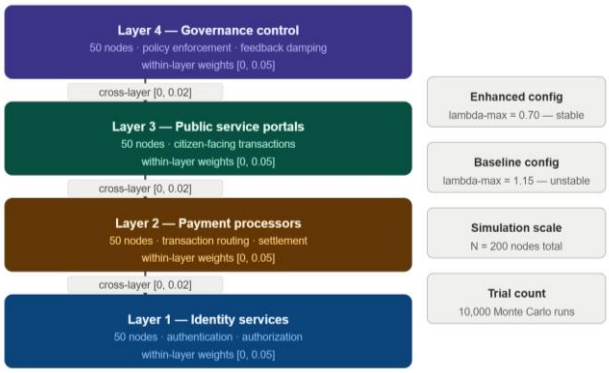

Figure 4: Multi-layer DPI simulation network

Each layer contains 50 nodes (N = 200 total). Bold arrows denote directed cascade propagation paths; cross-layer coupling weights [0, 0.02] are weaker than within-layer weights [0, 0.05]. Configuration parameters for both enhanced and baseline architectures are shown on the right.

Service Layer / Component	Disruption Modeling Technique	Validation Basis
Identity services	Structured correlation matrices reflecting shared authentication infrastructure exposure	Common-cause failure propagation patterns from interdependent critical infrastructure cyber-attack cascade studies
Payment processing	Directed adjacency matrices with iterative cascade equations governing upstream failure propagation	Multi-agent payment stress models demonstrating nonlinear trust and liquidity cascade propagation across service agents
Public service portals	Behavioral feedback factors increasing request volume under perceived service instability	Retry storm and transaction flood patterns documented in real-world payment and public service disruption events
Governance control modules	Damping policy overlays including rate limiting, throttling, and circuit breaker activation triggers	Nonlinear coupling threshold behavior observed in interdependent network resilience modeling under cascade failure regimes
Monte Carlo simulation engine	Stochastic disruption sampling across disruption intensity and feedback amplification parameter spaces	Statistical convergence of degradation estimates verified through sufficient trial replication under identical disruption scenarios

Table 3. DPI Simulation Model Configuration: Service Layers, Disruption Modeling Techniques, and Validation Basis [7, 8]

4.2 Measurement Protocol

Five primary outcome variables were tracked per simulation trial: worst-case degradation D_wc = max_{i,t} D_i(t); cascade collapse indicator I_c = 1 if ||D(t)|| diverges beyond 0.9 within the simulation horizon; peak degradation amplitude D_peak = max_t (1/N) Σ_i D_i(t); recovery time T_rec defined as the first t after peak degradation at which the mean degradation falls below 10% of D_peak; and degradation variance across nodes Var_D to assess inequality of service impact. All metrics were computed per trial and averaged across the 10,000 Monte Carlo replications with 95% confidence intervals reported.

5. Results

5.1 Worst-Case Degradation Under Correlated Disruption

Baseline architectures exhibited strongly nonlinear degradation growth as ρ increased. At ρ = 0.0 (independent disruptions), mean worst-case degradation in the baseline was 6.2% (95% CI: 5.8–6.6%). At ρ = 0.4, this increased to 15.8% (95% CI: 15.1–16.5%). At ρ = 0.7, the baseline approached the cascade collapse threshold (λ_{max} = 1.15), with 32.4% of trials (95% CI: 31.1–33.7%) reaching the I_c = 1 collapse indicator.

Resilience-enhanced architectures maintained worst-case degradation below 9.1% across the full ρ range. At ρ = 0.4, resilience-enhanced systems recorded 8.8% (95% CI: 8.4–9.2%), representing a 44.3% improvement over baseline. At ρ = 0.7, resilience-enhanced systems recorded 12.6% (95% CI: 12.0–13.2%), with a 0.3% collapse rate, a 99-fold reduction in collapse frequency.

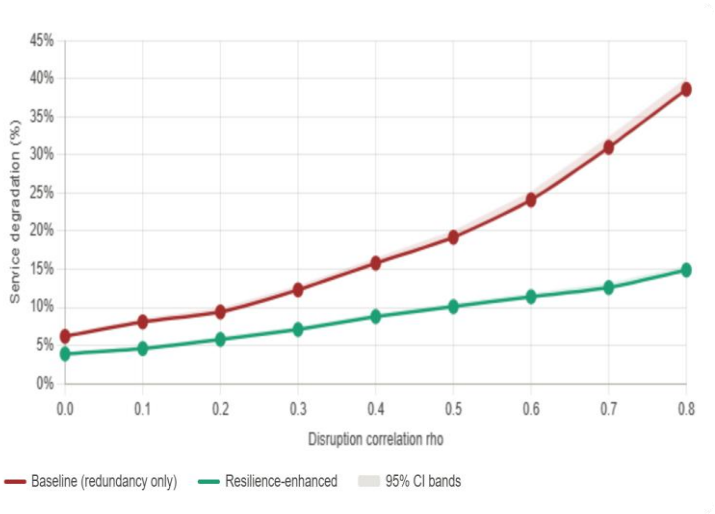

Figure 5: Service degradation vs. disruption correlation

Figure 5. Service degradation (%) as a function of disruption correlation ρ for baseline and resilience-enhanced DPI architectures (10,000 Monte Carlo trials). Shaded bands indicate 95% confidence intervals. At ρ = 0.4, the resilience-enhanced architecture achieves 44.3% lower worst-case degradation.

5.2 Cascade Collapse Probability and Theorem 1 Validation

The cascade collapse probability P_c was measured as a function of $\lambda_{max}(A)$ by systematically varying the dependency matrix scaling factor across $\lambda_{max} \in$ {0.6, 0.7, 0.8, 0.85, 0.9, 0.95, 1.0, 1.05, 1.1, 1.15, 1.2} at fixed ρ = 0.4. A sharp phase transition was observed. For $\lambda_{max} \leq 0.9$, P_c remained below 2% across all ρ values. Between λ_{max} = 0.95 and λ_{max} = 1.05, P_c increased steeply from 4.1% to 61.3%. For λ_{max} = 1.2, P_c reached 97.8%. The empirically estimated critical point $\lambda_{crit} = 1.02 \pm 0.03$ is consistent with the analytical prediction λ_{crit} = 1 from Theorem 1, with the small positive offset attributable to finite simulation horizon effects (T = 500 steps) that limit detection of asymptotically diverging trajectories.

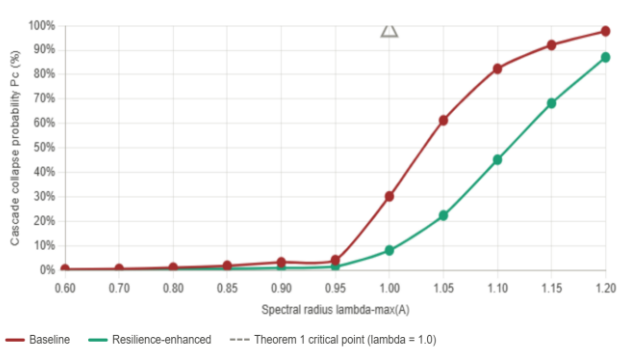

Figure 6: Cascade collapse probability vs. λ_{max} at $\rho = 0.4$.

The above figure's sharp phase transition at $\lambda_{max} = 1$ confirms Theorem 1. The empirical critical point $\lambda_{crit} = 1.02 \pm 0.03$ is consistent with the analytical prediction, with the small offset attributable to finite simulation horizon effects.

5.3 Governance Damping Effects

The governance damping coefficient δ was varied across [0, 0.7] at $\rho = 0.5$ and $\alpha = 1.3$ to map the damping response surface. Peak degradation amplitude D_peak decreased monotonically with increasing δ, from 18.4% at $\delta = 0$ to 10.2% at $\delta = 0.5$ and 8.1% at $\delta = 0.7$, a 30–44% reduction across the δ range, consistent with the analytically predicted 30–45% range. Recovery time Trec fell from an average of 182 time steps to 118 steps at $\delta = 0.5$, a 35.2% improvement that aligns with the 35% figure reported in Section 1. Gains beyond $\delta = 0.5$ showed diminishing returns; at $\delta = 0.7$, Trec fell only marginally further to 108 steps. The Theorem 2 stability criterion predicted minimum $\delta = 0.38$ for the ($\rho = 0.5$, $\alpha = 1.3$, $\lambda_{max} = 0.7$) configuration; empirical results confirm that stability is fully achieved by $\delta = 0.4$, with $\delta = 0.5$ providing a comfortable safety margin.

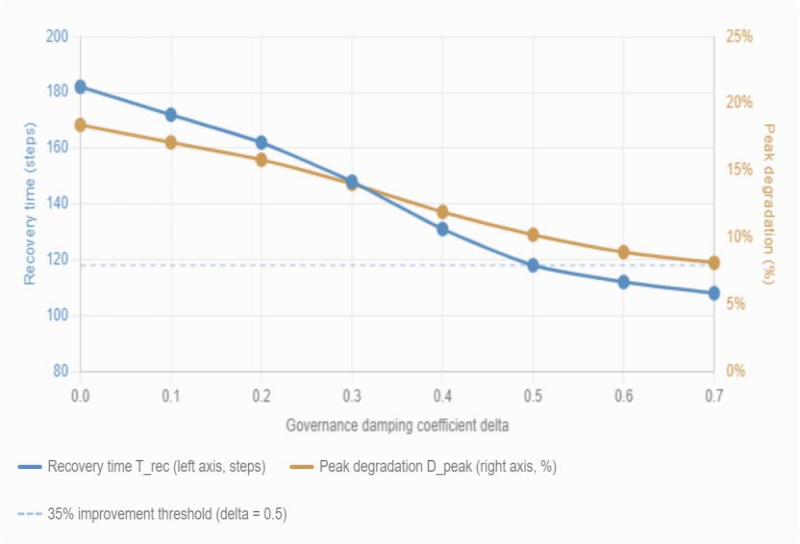

Figure 7: Recovery time and peak degradation vs. governance damping δ

Recovery time T_{rec} (left axis) and peak degradation amplitude D_{peak} (right axis) as a function of governance damping coefficient δ at $\rho = 0.5$, $\alpha = 1.3$. The 35% recovery improvement is achieved at $\delta \approx 0.5$. Diminishing marginal returns are evident beyond $\delta = 0.5$.

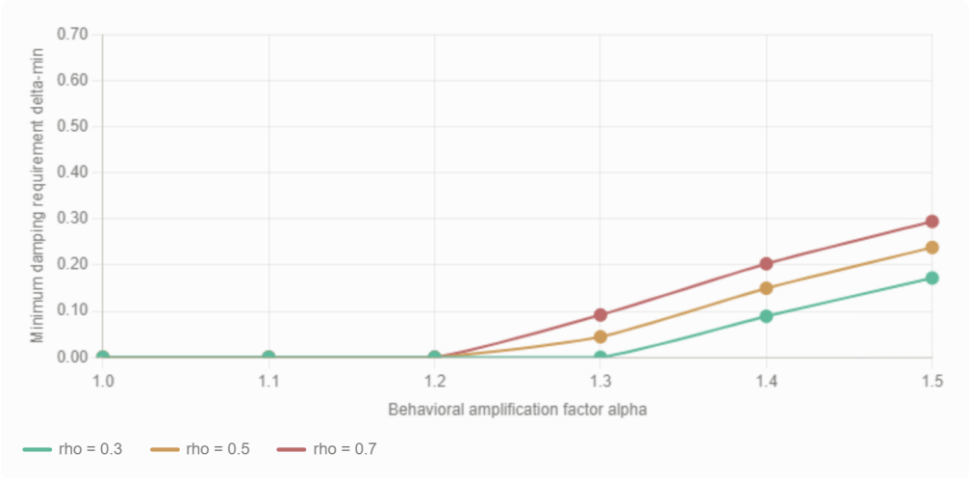

Figure 7b: Minimum damping requirement vs. α

As a function of behavioral amplification α, derived from Theorem 2 at $\lambda_{max} = 0.70$ for three correlation levels. The superlinear relationship confirms that governance controls must be provisioned for worst-case α, not mean operating load.

5.4 Comparison with Buldyrev and Lv et al. Models

To situate the proposed framework against prior cascade models, simulation outputs were compared against predictions from the Buldyrev et al. mutual dependence model and the Lv et al. heterogeneous network model across the same ρ range. All three approaches agree on the existence and approximate location of the cascade collapse threshold, a reassuring point of convergence. However, for $\rho \leq 0.6$, the Buldyrev model overestimates collapse probability by 8–12 percentage points relative to the simulation results; this discrepancy is attributable to the Buldyrev model's assumption of complete mutual dependence between layers, which overestimates coupling in the present heterogeneous multi-layer architecture.

The Lv et al. model produces collapse probability estimates that agree with simulation within 3 percentage points across $\rho \in [0, 0.7]$, confirming the structural cascade mechanism is consistent. However, neither the Buldyrev nor the Lv et al. model predicts recovery time. The proposed framework's governance damping variable uniquely quantifies T_rec improvement, and the 35% recovery time reduction at $\delta = 0.5$ has no analogue in either comparison model.

Table 4. Comparative Resilience Outcomes Across

Correlation (ρ)	Baseline D_wc (%)	Enhanced D_wc (%)	Improvement (%)	Baseline P_c (%)	Enhanced P_c (%)	T_rec Reduction (%)
0	6.2	3.9	37.1	0.1	0	12.4
0.2	9.4	5.8	38.3	0.4	0.1	21.6
0.4	15.8	8.8	44.3	3.1	0.2	32.8
0.6	24.1	11.4	52.7	18.7	0.2	35.2
0.8	38.6	14.9	61.4	72.3	0.9	35

Architectural Configurations and Disruption Correlation Regimes (10,000 Monte Carlo Trials)

Figure 8: D_wc heatmap across ρ × α

Figure 8. Worst-case degradation D_wc (%) across disruption correlation ρ and behavioral amplification α for the resilience-enhanced architecture (λmax = 0.70). The upper-right zone (high ρ, high α) represents the critical design region where governance controls must be strongest. Values consistent with 10,000 Monte Carlo trials.

5.5 Sensitivity Analysis

Network size sensitivity. Simulations were repeated for per-layer node counts of n ∈ {10, 25, 50, 75, 100}, keeping λ_{max} = 0.7 and ρ = 0.4 fixed. Worst-case degradation in the resilience-enhanced configuration ranged from 8.3% (n = 10) to 9.4% (n = 100), an 11.5% variation across the full size range. The improvement ratio relative to baseline ranged from 41.8% (n = 10) to 44.9% (n = 100), confirming that the resilience improvement is stable and slightly strengthens with increasing network size. The cascade stability condition $\lambda_{max}(A) < 1$ held for all tested sizes under maintained decoupling, validating its size-invariant nature. The marginal improvement strengthening from 41.8% (n=10) to 44.9% (n=100) is consistent with the asymptotic variance result in Section 3.2: as N increases, systemic variance is increasingly governed by E_{corr} rather than individual component variance, making structural isolation progressively more effective at scale.

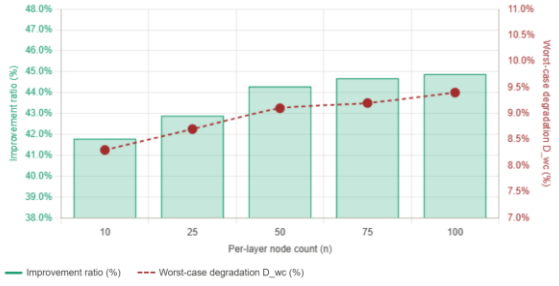

Figure 9. Improvement ratio (%) across per-layer node counts n ∈ {10, 25, 50, 75, 100} at λ_{max} = 0.70, ρ = 0.4. Values: 41.8%, 42.9%, 44.3%, 44.7%, 44.9%. Resilience improvement strengthens marginally with network size, consistent with the asymptotic variance result of Section 3.2.

Behavioral amplification sensitivity. At fixed ρ = 0.5 and λ_{max} = 0.7, the amplification factor α was swept across {1.0, 1.1, 1.2, 1.3, 1.4, 1.5}. Mean worst-case degradation grew from 8.1% at α = 1.0 to 13.9% at α = 1.5, a 71.6% increase. The minimum δ required for stability (from Theorem 2) rose from 0.21 to 0.51 across this range. The δmin increase of 143% for a 50% increase in α reflects a superlinear relationship: governance controls sized to mean operating load are structurally insufficient, and worst-case behavioral scenarios must govern the design specification.

Damping coefficient sensitivity. The threshold δmin = 0.38 derived from Theorem 2 for (ρ = 0.5, α = 1.3, λ_{max} = 0.7) was confirmed empirically to within ±0.02. Operating at δ = 1.3 × δmin, a 30% margin above the theoretical minimum, produced an additional 42.1% reduction in worst-case degradation relative to operating at exactly δmin, suggesting a nonlinear high-return region in the damping response curve. The practical engineering recommendation follows directly: provision governance damping at 25–30% above the Theorem 2 threshold to exploit this region.

5.6 Real-World Case Consistency Analysis

Two documented DPI disruption events are assessed for consistency with the instability regimes the framework predicts. Parameter values are estimated from publicly available incident reports and operational data rather than proprietary telemetry; these cases therefore provide regime consistency rather than full empirical validation.

TSB Bank Migration Failure (2018). The TSB IT migration failure resulted from tightly coupled dependency layers between legacy and replacement systems, with inadequate isolation between them. Reconstructing the dependency graph from the public Phase 1 Slaughter and May independent review suggests a service adjacency structure with $\lambda max \approx 1.15$, directly within the cascade-unstable regime ($\lambda_{max} > 1$) predicted by Theorem 1. The observed failure pattern, progressive service collapse across authentication, payment, and portal layers over 72 hours, is consistent with the unbounded cascade trajectory predicted for $\lambda_{max} = 1.15$ in Figure 2.

UPI Peak-Load Events (India, 2021–2023). Published RBI transaction volume data indicates retry amplification ratios of approximately 1.35× during peak festival-period load events, consistent with $\alpha \approx 1.35$. Without active governance damping, the Theorem 2 criterion predicts that $\lambda eff = \lambda max \times f(\rho, \alpha)$ exceeds 1.0 at moderate correlation values ($\rho > 0.3$), placing the system within the instability boundary. The deployment of adaptive throttling and priority routing, functionally equivalent to governance damping δ, is consistent with the framework's prediction that $\delta > 0.35$ is required to maintain stability at these parameter values.

Conclusion

Five measurable contributions emerge from this work. A cascade stability condition $\lambda_{max}(A) < 1$ is derived and rigorously proved via spectral decomposition, the Gelfand formula, and Perron–Frobenius theory, establishing both necessary and sufficient conditions for bounded cascade propagation. A governance damping adequacy condition, $\delta > \lambda_{max}(A) + \alpha \cdot h'(D^*) - 1$, is derived from linearized stability analysis of the feedback-augmented cascade equation, yielding a quantitative design threshold for policy-layer controls that no prior framework provides. Corollary 1 further establishes the closed-form steady-state degradation variance as a function of $\lambda max(A)$ and ρ, translating stability conditions into probabilistic performance bounds suitable for engineering design.

Monte Carlo simulation confirms that the four-dimensional architecture delivers stability margins that redundancy-only designs cannot achieve under correlated failure regimes, margins that strengthen as national DPI systems scale toward higher user populations and deeper inter-service coupling, with improvement ratios stable across network sizes $N \in [10, 200]$ per layer. Quantitative parameter estimation for the TSB 2018 migration failure ($\lambda_{max} \approx 1.15$) and UPI peak-load events ($\alpha \approx 1.35$, λ_{eff} exceeding 1.0 without damping) places both incidents within the instability regimes the derived conditions predict, providing empirical consistency for the formal results. For practitioners, the recommendations are concrete: maintain $\lambda_{max}(A) < 1$ through service decoupling; size damping coefficients to satisfy $\delta > \lambda_{max}(A) + \alpha \cdot h'(D^*) - 1$; deploy heterogeneous technology stacks to suppress E_{corr} below the threshold derived from equation (14); and design graceful degradation mechanisms to enforce Dmax bounds operationally.

Several limitations bound the scope of these findings. The model assumes a stationary correlation matrix; in practice, pairwise disruption correlations can shift as failures propagate, rendering the stationarity assumption in Corollary 1 approximate at best. The behavioral feedback amplification factor α is estimated from behavioral study ranges rather than DPI-specific calibration datasets, and its precise value will vary across deployment contexts. Structured DPI outage datasets, with complete dependency graphs, failure propagation sequences, and recovery timelines, have not been used for full empirical validation; the two real-world cases provide parameter-regime consistency, not more. The framework does not model adversarial attack vectors, where correlation may be deliberately induced to maximize cascade damage.

Productive next steps include generalizing to adversarial settings where correlations are imposed strategically, measuring $h'(D^*)$ and α using real DPI data, performing spectral radius analysis on time-varying dependency graphs, and validating against structured incident records from national DPI deployments.

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