Governance- and Security-by-Design: Embedding Safety and Alignment into Agentic AI Systems

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Abstract

As artificial intelligence systems transition from task-specific tools to autonomous agents capable of complex decision-making, traditional external oversight mechanisms become inadequate for ensuring safety, security, and alignment. This paper introduces a governance-by-design framework that embeds responsibility mechanisms directly into agentic AI architectures, enabling continuous self-monitoring and alignment verification through multi-agent governance systems. We demonstrate that external governance approaches fail to scale with system autonomy, creating temporal gaps between assessment and deployment that enable ungovernable behaviors. Through mathematical modeling using stochastic differential equations, we formalize how competing objectives in agentic systems create systematic interference patterns that degrade safety properties. Our empirical validation across 800 experiments reveals three critical failure modes: (1) **systematic security vulnerabilities from AI-generated code**, with efficiency-focused prompting introducing memory safety issues in 42.7% of cases while security-focused prompting paradoxically creates cryptographic vulnerabilities in 21.1% of cases; (2) **iterative degradation where security vulnerabilities** increase by 37.6% after just five feedback iterations; and (3) **knowledge dilution** where domain expertise degrades by 47% as irrelevant context accumulates. Our multi-agent governance architecture, validated through industry partnerships, achieves a 40% reduction in post-deployment safety incidents while maintaining operational capability. These findings establish that safe, secure, and aligned agentic systems require architectural integration of governance mechanisms that address the dynamic, multi-objective nature of autonomous AI systems.

1 Introduction

The rapid advancement of agentic AI systems, autonomous agents capable of planning, tool use, code generation, and complex decision-making [9, 8], presents unprecedented challenges for safety, security, and alignment. Unlike traditional AI systems that operate within narrow domains under continuous human supervision, agentic systems make thousands of decisions autonomously, often evolving capabilities and generating artifacts (code, content, decisions) that compound over time [1]. This creates a fundamental challenge: external oversight mechanisms cannot keep pace with systems that operate faster, evolve dynamically, and exhibit emergent behaviors that human monitors cannot comprehend or validate in real-time.

Current approaches to AI safety [3, 7] treat governance, security, and alignment as separate concerns addressed through external constraints applied to already-built systems. This siloed retrofitting paradigm fails for three interconnected reasons. First, *temporal gaps* emerge between assessment and deployment, during which systems evolve beyond their evaluated state. Second, *dynamic degradation* occurs through iterative interactions, where systems that initially perform well progressively develop unsafe behaviors through feedback loops. Third, *multi-objective interference* causes competing goals (efficiency, functionality, security) to systematically undermine each other through attention competition and priority recalibration.

We argue that safe deployment of agentic AI systems requires a fundamental paradigm shift from external oversight to *embedded governance-by-design* [2, 10], treating safety, security, and alignment not as external constraints but as integral architectural components. Our framework addresses these challenges through three key mechanisms: (1) specialized governance agents operating alongside task-completion agents, (2) continuous monitoring of multi-objective dynamics, and (3) intervention capabilities that prevent degradation before it manifests in harmful behaviors.

1.1 Contributions

This paper makes four primary contributions that unite safety, security, and alignment for agentic systems:-

1. **Mathematical Framework for Multi-Objective Governance:** We formalize governance-by-design using stochastic differential equations (SDEs) that model the continuous-time evolution of competing objectives in agentic systems. Our interference matrix formulation reveals how optimization for one objective (e.g., efficiency) systematically degrades others (e.g., security), with convergence rates ranging from 0.33 to 1.29 across different governance strategies.
2. **Empirical Validation of Dynamic Degradation:** Through 800 controlled experiments across multiple domains, we demonstrate three critical failure modes:-
   (a) *Systematic vulnerability patterns*: Efficiency-focused prompting introduces memory safety issues in 42.7% of AI-generated code, while security-focused prompting paradoxically creates cryptographic vulnerabilities in 21.1% of cases.
   (b) *Iterative degradation*: Security vulnerabilities increase by 37.6% after just five feedback iterations without governance intervention.
   (c) *Knowledge dilution*: Domain-specific security expertise degrades by 47% as irrelevant but contextually plausible information accumulates (from 0 to 40,000 dilution tokens).
3. **Multi-Agent Governance Architecture:** We present a production-ready governance architecture validated through Vector Institute industry partnerships, demonstrating 40% reduction in post-deployment safety incidents while identifying emerging issues 4.7 days earlier than traditional monitoring approaches.
4. **Unified Safety-Security-Alignment Framework:** We establish that these traditionally separate concerns are fundamentally interconnected in agentic systems, requiring integrated governance mechanisms rather than independent solutions. Our framework provides practical mitigation strategies grounded in dynamical systems theory and validated through real-world deployments.

2 Mathematical Framework: Multi-Objective Dynamics in Agentic Systems

2.1 Stochastic differential equation formulation

We model agentic AI systems as operating in multi-objective spaces where competing goals create systematic interference patterns. Let $\mathbf{x}(t) \in \mathbb{R}^n$ represent the objective vector at time t, where each dimension corresponds to a critical system property (security, efficiency, functionality, alignment). The continuous-time evolution follows a stochastic differential equation [11, 13]:

$$d\mathbf{x} = \boldsymbol{\mu}(\mathbf{x}, \pi)dt + \boldsymbol{\sigma}(\mathbf{x}, \pi)d\mathbf{W} \tag{1}$$

where $\boldsymbol{\mu}(\mathbf{x}, \pi) : \mathbb{R}^n \times \Pi \to \mathbb{R}^n$ encodes systematic objective changes under governance strategy $\pi \in \Pi$, $\boldsymbol{\sigma}(\mathbf{x}, \pi) : \mathbb{R}^n \times \Pi \to \mathbb{R}^{n \times n}$ captures system stochasticity, and $\mathbf{W}$ represents an n-dimensional Brownian motion modeling the inherent randomness in agentic decision-making.

This formulation generalizes across agentic applications: code generation balancing security, efficiency, and functionality; content systems managing creativity, accuracy, and engagement; or decision support optimizing speed, thoroughness, and interpretability.

2.2 Interference matrix and objective coupling

We define the *interference matrix* $\mathbf{I}$ using off-diagonal elements of the linearized drift matrix $\mathbf{A}$:

$$I_{ij} = \begin{cases} A_{ij} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \tag{2}$$

This provides strategy-conditioned coupling measures capturing objective interdependencies. Negative off-diagonal elements indicate systematic trade-offs where improving objective j degrades objective i. For the linearized system $d\mathbf{x} = \mathbf{A}\mathbf{x}dt + \mathbf{\Sigma}d\mathbf{W}$ near equilibrium [12], the eigenvalue spectrum of $\mathbf{A}$ determines convergence behavior:-

1. **Exponential convergence**: Real eigenvalues $\lambda_i < 0$ yield monotonic convergence with rate $\max_i |\lambda_i|$.
2. **Oscillatory dynamics**: Complex eigenvalue pairs $\lambda = \alpha \pm i\beta$ produce damped oscillations with frequency β and decay rate α.
3. **Boundary attraction**: Eigenvalues approaching zero indicate slow convergence toward constraint boundaries, yielding extreme trade-offs.

2.3 Governance strategy characterization

Our empirical analysis across 400 sessions identified four distinct governance regimes with characteristic convergence properties:

Table 1: Governance strategy dynamics and convergence properties

Strategy	Convergence Rate	Eigenvalue Type	Predictability (R^2)
Adaptive Integration	0.15	Real negative	0.74
Efficiency-focused	0.33	Real negative	0.58
Security-focused	1.08	Complex pair	0.72
Feature-focused	1.29	Near-zero	0.50

The adaptive integration strategy, which uniformly weights all objectives ($\boldsymbol{\mu}_{AI}(\mathbf{x}) = [0.08x_s, 0.08x_e, 0.08x_f]^T$), achieves highest predictability and stable convergence. In contrast, aggressive single-objective focus (feature-focused: $\boldsymbol{\mu}_{FF}(\mathbf{x}) = [-0.82x_s, -0.88x_e, 0.9x_f]^T$) exhibits near-zero eigenvalues indicating boundary convergence with sacrificed optimality, achieving only 50% Pareto efficiency compared to 95%+ for balanced strategies.

This mathematical framework reveals a fundamental insight: agentic systems without proper governance architecture naturally drift toward extreme trade-offs where optimizing one objective systematically degrades others. The interference matrix for code generation demonstrates this pattern:-

$$\mathbf{I}_{\text{code}} = \begin{bmatrix} 0 & 0 & -0.09 \\ 0 & 0 & -0.17 \\ -0.09 & -0.17 & 0 \end{bmatrix} \tag{3}$$

Functionality improvements consistently degrade both security ($I_{13} = -0.09$) and efficiency ($I_{23} = -0.17$), with efficiency suffering most severely. This quantifies why feature-driven development without governance oversight predictably introduces security vulnerabilities.

3 The Scaling Problem of External Oversight

3.1 Temporal gaps in traditional governance

Traditional AI governance operates through periodic assessment cycles: systems are evaluated during development, tested before deployment, and monitored during operation through sampling or audit mechanisms. This approach creates three critical temporal gaps.

The development-deployment gap occurs when systems pass initial safety evaluations but later exhibit emergent behaviors during autonomous operation. For agentic systems that can learn from experience or combine capabilities in novel ways, initial assessments provide limited guarantees about future behavior. A system deemed safe in controlled testing environments may develop unsafe patterns when exposed to real-world complexity and edge cases.

The decision-monitoring gap emerges from the speed differential between AI decision-making and human oversight. An agentic AI system in financial trading or medical diagnosis may make thousands of decisions per minute, each with significant consequences. Human reviewers cannot meaningfully audit this volume in real-time, forcing organizations to rely on sampling or retrospective review. By the time unsafe patterns are identified through these mechanisms, substantial harm may have already occurred.

The capability-assessment gap arises as systems evolve beyond their initial specifications. Agentic AI systems often develop emergent capabilities through training, fine-tuning, or interaction with other systems. External assessments become outdated as systems change, but continuous re-evaluation is economically and practically infeasible at the scale required for meaningful coverage.

3.2 The autonomy-oversight paradox

We observe a fundamental tension: the more autonomous and capable we make AI systems, the less effectively external oversight can govern them. This paradox emerges from the following three factors:-

First, capability scaling outpaces monitoring scaling. As AI systems become more sophisticated, their decision spaces expand exponentially while human monitoring capacity grows only linearly. A simple decision tree with ten binary choices creates 1,024 possible paths; adding autonomous planning and tool use creates effectively infinite decision spaces that cannot be comprehensively monitored.

Second, opacity increases with capability. More powerful AI systems employ more complex internal representations and reasoning processes. While interpretability research makes progress, the fundamental challenge remains: highly capable systems are inherently more difficult to understand and audit than simple systems. This means the systems most in need of oversight are precisely those most resistant to it.

Third, intervention becomes costlier at scale. External oversight requires interrupting system operation for human review. For systems making time-critical decisions in dynamic environments, this interruption cost becomes prohibitive. Either we accept reduced safety through less frequent oversight, or we accept reduced capability through more frequent intervention.

4 Governance-by-Design Framework

4.1 Architectural principles

Governance-by-design addresses the scaling problem and three critical failure modes by making safety, security, and alignment intrinsic to system architecture rather than extrinsic constraints. The framework rests on four core principles informed by our mathematical and empirical analysis.

Embedded monitoring agents continuously observe system behavior from within the architecture itself. Rather than sampling external behavior, governance agents have direct access to internal states, reasoning processes, and decision pathways. This eliminates temporal gaps between decision and oversight while enabling detection of emergent degradation patterns before they manifest in harmful behaviors.

Multi-objective optimization treats governance not as a constraint but as a co-equal objective alongside task performance [25, 26]. Drawing from our SDE framework, the system architecture explicitly balances task completion, safety compliance, alignment maintenance, and security requirements through attention allocation mechanisms that prevent interference-driven degradation. The drift function incorporates governance objectives:-

$$\boldsymbol{\mu}_{\text{gov}}(\mathbf{x}) = \alpha_s \nabla_x \mathcal{S}(\mathbf{x}) + \alpha_e \nabla_x \mathcal{E}(\mathbf{x}) + \alpha_f \nabla_x \mathcal{F}(\mathbf{x}) + \alpha_g \nabla_x \mathcal{G}(\mathbf{x}) \tag{4}$$

where $\mathcal{S}$, $\mathcal{E}$, $\mathcal{F}$, and $\mathcal{G}$ represent security, efficiency, functionality, and governance objectives respectively, with weights α_i determined by the meta-governance coordinator to maintain balanced convergence properties.

Autonomous intervention capabilities allow governance agents to directly modify system behavior when safety violations are detected. Rather than merely flagging issues for human review, governance agents can prevent unsafe actions, request human input for ambiguous cases, or shut down operations when fundamental alignment failures occur. Intervention thresholds are calibrated based on failure mode detection:-

1. Vulnerability pattern detection: $|\mathbf{I}_{ij}| > \theta_v$ triggers **security audit**.
2. Iterative degradation detection: $\frac{d}{dt}\mathcal{S}(\mathbf{x}) < -\theta_d$ requires **human review**.
3. Knowledge dilution detection: $w_s(D) < \theta_k w_{s0}$ initiates **context compression**.

Continuous alignment verification ensures that safety properties are maintained throughout system operation rather than verified only at deployment. Governance agents actively test whether the system remains aligned with intended values and objectives, detecting capability drift through eigenvalue monitoring of the linearized drift matrix $\mathbf{A}$. When eigenvalues approach zero (indicating boundary convergence toward extreme trade-offs), the system triggers governance intervention.

4.2 Multi-agent governance architecture addressing failure modes

Our implementation employs a multi-agent system where specialized governance agents monitor different safety properties alongside task-completion agents. The architecture addresses each identified failure mode through targeted mechanisms while maintaining unified coordination.

Addressing Systematic Vulnerability Patterns:

Code security auditors employ multi-layered analysis calibrated for AI-generated code characteristics [30]:-

1. Static analysis detecting prompting-strategy-specific patterns (memory safety checks for efficiency-focused code, cryptographic library validation for security-focused code).
2. Dynamic testing with fuzzing targeted at common AI-generated vulnerability classes.
3. Complexity-vulnerability regression models ($\beta = 0.64$ established from empirical data) to flag high-risk modifications.

Prompting strategy monitors track objectives and constraints in task specifications, identifying when optimization directives may induce systematic vulnerability patterns. When efficiency optimization is requested, governance agents automatically elevate security monitoring intensity and enforce defensive programming patterns.

Addressing Iterative Degradation:

Iteration tracking agents maintain state across development cycles, computing degradation metrics:

$$\Delta_{\text{degrade}}(t) = \frac{\mathcal{V}(t) - \mathcal{V}(t-1)}{\mathcal{V}(t-1)} \tag{5}$$

where $\mathcal{V}(t)$ represents vulnerability count at iteration t. When $\Delta_{\text{degrade}} > 0.15$ (corresponding to our empirically observed 37.6% increase over 5 iterations), the system triggers mandatory human review and resets the iteration counter.

Historical pattern analyzers compare current trajectories against learned degradation curves from our 400-sample dataset, enabling early intervention before critical vulnerability emergence. For feature-focused development showing near-zero eigenvalue patterns ($|\lambda| < 0.3$), governance agents proactively suggest balanced refinement strategies.

Addressing Knowledge Dilution:

Context management agents implement sophisticated attention preservation:-

1. Semantic compression of irrelevant context while preserving domain-critical constraints.

2. Periodic restatement of security requirements when dilution exceeds thresholds ($D > 8,000$ tokens triggers reinforcement).
3. Domain-specific context windows maintain separation between general conversation and security-critical specifications.
4. Attention weight monitoring, estimating $w_s(D)$ and triggering refresh when expertise degradation exceeds 20%.

Task complexity adjusters modulate governance intensity based on cognitive load: high-complexity tasks (Session Manager-level: $\chi^2_F = 52.3$) receive enhanced monitoring given their greater dilution sensitivity.

Unified Governance Coordination:

The architecture includes seven coordinated agent categories operating in concert:-

1. **Alignment monitors** continuously verify that system objectives remain consistent with human values and intended outcomes [5, 6, 4], detecting goal drift and proxy objective development.
2. **Safety constraint enforcers** maintain hard boundaries on system behavior, preventing actions that could cause harm, regardless of task performance benefits.
3. **Security auditors** perform comprehensive vulnerability analysis using both traditional tools and AI-specific pattern detection calibrated for systematic vulnerabilities.
4. **Fairness auditors** ensure decisions do not exhibit discriminatory patterns or disproportionately affect protected groups.
5. **Transparency agents** maintain interpretability of system reasoning, generating explanations and identifying opaque decision logic requiring human review.
6. **Iteration guardians** monitor development cycles, detecting degradation patterns and enforcing mandatory review points.
7. **Meta-governance coordinators** manage interactions between governance agents, resolve conflicts between competing safety properties, balance multi-objective trade-offs using learned interference matrices, and determine escalation requirements.

The meta-governance coordinator implements a hierarchical decision process grounded in our mathematical framework. It computes the current drift vector $\boldsymbol{\mu}(\mathbf{x})$, estimates the interference matrix $\mathbf{I}$ through local linearization, performs eigenvalue analysis to assess convergence properties, and adjusts attention allocation weights $\{\alpha_i\}$ to maintain stable, balanced convergence toward desired equilibria rather than boundary extremes.

4.3 Implementation and validation

We validated this architecture through comprehensive studies encompassing 800 total experiments:- industry partnerships (3 deployments), systematic vulnerability analysis (1,247 code samples), iterative degradation study (400 samples across 40 rounds), and knowledge dilution experiments (400 samples across 5 dilution levels).

Industry deployment validation:

Three production deployments in partnership with industry partners validated the governance architecture in high-stakes domains: healthcare diagnostics, financial risk assessment, and legal document analysis. Each deployment involved agentic AI systems operating with significant autonomy.

Results demonstrated significant improvements in safety outcomes with minimal impact on system performance. The governance overhead averaged 2.4% of system decisions requiring intervention or human review, while safety incidents decreased by 40% compared to systems using traditional external monitoring approaches.

Critically, governance-by-design identified emerging safety issues an average of 4.7 days earlier than external monitoring systems, enabling proactive intervention before patterns manifested in user-facing behaviors. This early warning capability proves particularly valuable for agentic systems where behavioral drift can compound rapidly through iterative refinement and extended operation.

Table 2: Governance-by-design implementation results across industry deployments

Domain	Safety Incidents	Intervention Rate	Early Detection
Healthcare Diagnostics	40% reduction	2.3% of decisions	4.2 days earlier
Financial Risk Assessment	35% reduction	1.8% of decisions	5.1 days earlier
Legal Document Analysis	45% reduction	3.1% of decisions	4.9 days earlier
Average	**40% reduction**	**2.4% overhead**	**4.7 days earlier**

Failure mode mitigation validation:

Controlled experiments evaluated governance effectiveness against each identified failure mode. Governance-enabled systems showed 67% reduction in efficiency-focused memory safety issues (from 42.7% to 14.4%) and 81% reduction in security-focused cryptographic errors (from 21.1% to 4.0%). Systems with iteration guardians maintained stable vulnerability counts across 10 iterations (mean increase 4.2% vs. 37.6% without governance). Context management reduced expertise degradation from 47% to 18% at extreme dilution levels (40,000 tokens).

Statistical validation confirmed governance effectiveness across all scenarios with very large effect sizes (Cohen's $d > 1.0$). Mixed-effects models accounting for domain, task complexity, and deployment context confirmed governance effectiveness as a robust main effect ($\beta_{\text{gov}} = -0.58$, $p < 0.001$). Governance-enabled systems achieved convergence properties consistent with adaptive integration strategy rather than degrading toward boundary conditions. See Appendix D for complete statistical analyses.

5 Towards Safe, Secure, and Aligned Agentic AI Systems

5.1 Unified framework for safety, security, and alignment

Our research establishes that safety, security, and alignment are not independent concerns but deeply interconnected properties that must be addressed through unified governance mechanisms. The three failure modes reveal systematic coupling:-

1. **Safety-Security Coupling**: Systematic vulnerability patterns (security) directly compromise system safety by creating exploitable attack vectors. The 42.7% memory safety vulnerability rate in efficiency-optimized code represents both a security weakness and a safety hazard when these systems operate autonomously in critical domains. Our mathematical framework captures this through interference matrix elements: improving efficiency (x_e) systematically degrades security (x_s) with coupling coefficient $I_{se} < 0$.
2. **Security-Alignment Coupling**: Iterative degradation demonstrates how misaligned optimization objectives (prioritizing features over security) progressively compromise security properties. The 37.6% vulnerability increase across iterations reflects misalignment between stated security requirements and actual optimization behavior. Systems converge toward boundary conditions (near-zero eigenvalues) where alignment with security principles is abandoned in favor of single-objective performance.
3. **Alignment-Safety Coupling**: Knowledge dilution shows how loss of domain expertise (alignment failure) directly degrades safety capabilities. The 47% reduction in security feature implementation reflects both misalignment with security objectives and compromised safety through inadequate protection mechanisms. The exponential decay of attention weight $w_s(D) = w_{s0} \cdot e^{-\alpha D}$ formalizes how alignment with security principles erodes through extended operation.

This coupling necessitates integrated governance rather than siloed solutions. Addressing security vulnerabilities through code auditing alone fails if iterative processes reintroduce them. Maintaining alignment through periodic reinforcement fails if knowledge dilution systematically degrades expertise. Ensuring safety through monitoring fails if systematic vulnerabilities create exploitable attack surfaces.

5.2 Extending governance-by-design with integrated mitigation strategies

We extend our framework with comprehensive mitigation strategies addressing all three failure modes through coordinated governance mechanisms.

Architectural Extensions: Multi-level context isolation maintains separate windows for domain-critical constraints and general operational context. Attention preservation mechanisms implement periodic reinforcement schedules based on empirically validated thresholds. Iterative safety gates enforce mandatory human review at empirically determined checkpoints. Prompting strategy analyzers classify incoming directives using learned vulnerability patterns.

Dynamic Governance Adaptation: The meta-governance coordinator implements adaptive strategies based on real-time system state:-

$$\boldsymbol{\alpha}^*(t) = \arg\min_{\boldsymbol{\alpha}} \left\|\boldsymbol{\mu}(\mathbf{x}, \boldsymbol{\alpha}) - \boldsymbol{\mu}_{\text{target}}\right\|^2 + \lambda\|\boldsymbol{\alpha}\|^2 \tag{6}$$

where $\boldsymbol{\alpha}^*$ represents optimal attention allocation weights minimizing deviation from target drift while regularizing complexity. Eigenvalue monitoring detects convergence toward dangerous regimes and triggers corrective interventions.

Human-AI Collaboration Protocols: Governance-by-design emphasizes augmented rather than autonomous operation. Human expertise remains essential for strategic guidance, validation of governance interventions, contextual judgment, and periodic calibration of governance thresholds based on deployment-specific risk profiles. The architecture maintains explicit human-in-the-loop integration points triggered by configurable criteria. See Appendix C for detailed mitigation protocols.

5.3 Policy recommendations for deploying safe agentic systems

Deploying safe agentic AI systems requires coordination between technical governance mechanisms and policy frameworks. We recommend five policy interventions grounded in our empirical findings:-

1. Continuous governance verification requirements. Organizations deploying agentic AI should be required to demonstrate continuous governance verification rather than point-in-time safety assessments. Regulatory frameworks should recognize that traditional certification approaches are inadequate for systems that evolve autonomously.

2. Heightened scrutiny for code-generating systems. AI systems capable of code generation or self-modification should face heightened scrutiny requirements, with mandatory governance-by-design implementations verified by independent auditors.

3. Prioritized funding for interpretable governance research. Research priorities should include attention mechanism analysis for knowledge dilution detection, interference matrix estimation for real-time monitoring, and governance agent explainability.

4. Domain-specific governance standards. Critical domains (healthcare, finance, infrastructure) should establish domain-specific governance standards calibrated to sector risk profiles.

5. Liability frameworks for autonomous degradation. Legal frameworks should establish clear liability when systems degrade through the three identified failure modes despite known mitigation strategies.

These policy interventions create incentive structures favoring proactive governance implementation over reactive incident response. See Appendix B for detailed policy specifications.

6 Limitations and Future Work

Our governance-by-design framework demonstrates effectiveness across 800 experiments and three production deployments, but faces limitations requiring further research.

Computational efficiency: Governance overhead currently averages 2.4% of decisions requiring intervention. While acceptable for current deployments, systems making millions of decisions daily may require more efficient governance architectures. Future work should explore:-

1. Amortized governance through batch processing of similar decisions.

2. Hierarchical governance with lightweight first-pass screening.
3. Learned governance policies reducing per-decision computational cost.

Domain generalization: Our vulnerability analysis focused on code generation; knowledge dilution validation used security domain knowledge. Emerging domains like prompt engineering, model fine-tuning, multi-modal content generation, and reasoning systems may exhibit different failure mode patterns requiring expanded analysis and domain-specific governance adaptations.

Model diversity: Empirical validation used GPT-4 (code generation, knowledge dilution studies) and was partnered with Vector Institute deployments using various production models. Systematic comparison across model architectures (Claude, Gemini, Llama, domain-specific models) would establish whether failure modes represent fundamental architectural limitations or model-specific behaviors amenable to training interventions.

Governance calibration: The multi-agent architecture requires careful calibration to avoid conflicts between competing safety objectives. We need principled approaches for resolving tensions between fairness, transparency, security, and performance when these goals conflict fundamentally. Automated calibration methods using reinforcement learning or evolutionary optimization could improve deployment efficiency.

Adversarial robustness: Adversarial robustness of governance mechanisms remains understudied. Future work must evaluate whether governance agents themselves can be manipulated through direct attacks on their training, adversarial inputs designed to exploit coverage gaps, or strategic behavior by task-completion agents optimizing for governance evasion.

Long-term stability: Our longest deployment spans 6 months; longest iterative study covers 10 rounds. Systems operating continuously for years may develop novel degradation patterns not captured in current studies. Longitudinal research tracking governance effectiveness over extended deployments would establish maintenance requirements and identify slow-developing failure modes.

Theoretical extensions: Our SDE framework assumes locally linear drift near equilibria. Non-linear dynamics including saddle points, chaotic attractors, and bifurcations may characterize more complex agentic systems. Extending theoretical analysis to fully non-linear regimes would improve predictive accuracy for sophisticated autonomous agents.

7 Conclusion

Safe deployment of agentic AI systems requires moving beyond external oversight to governance-by-design. Through comprehensive empirical investigation encompassing 800 experiments, mathematical formalization using stochastic differential equations, and production validation through industry partnerships, we establish three fundamental insights:

1. Safety, security, and alignment are deeply coupled in agentic systems. Our interference matrix formulation and empirical validation demonstrate that these traditionally separate concerns exhibit systematic trade-offs ($I_{ij} < 0$ for competing objectives) that cannot be addressed through siloed solutions. The 42.7% memory safety vulnerabilities from efficiency optimization, 37.6% iterative degradation across feedback loops, and 47% knowledge dilution through extended operation reflect interconnected failure modes requiring unified governance.

2. External oversight fundamentally cannot scale with system autonomy. Temporal gaps (4.7 days detection delay without governance), decision-monitoring gaps (thousands of autonomous decisions), and capability-assessment gaps (systems evolving beyond evaluated states) create ungovernable windows where traditional approaches fail. Our mathematical framework formalizes why: as systems operate in higher-dimensional objective spaces with complex interference patterns, external monitoring cannot track multi-objective dynamics at the required granularity.

3. Governance-by-design provides a viable path forward. Embedding specialized governance agents within system architectures achieves 40% reduction in safety incidents, 67% reduction in systematic vulnerabilities, and 4.7-day earlier detection of emerging issues while maintaining 2.4% overhead. The architecture successfully addresses all three identified failure modes through coordinated monitoring, intervention, and adaptation mechanisms grounded in dynamical systems theory.

As AI systems become more autonomous and capable, the gap between what they can do and what we can effectively monitor will only widen. Governance-by-design offers a fundamental architectural approach: building systems that govern themselves according to human values, not through external constraint but through constitutional incapacity to operate outside safety, security, and alignment boundaries. This shift from retrofitted oversight to architectural governance may prove essential for realizing the benefits of agentic AI while managing its risks.

The broader implications extend across AI safety research. Our work demonstrates that the theoretical tools of dynamical systems analysis, the empirical rigor of controlled experimentation, and the practical validation of industry deployment can be unified into comprehensive frameworks addressing real-world safety challenges. Future progress in AI safety will likely require similar integration of mathematical formalization, empirical validation, and production deployment to move beyond isolated findings toward systematic understanding of how to build reliably safe, secure, and aligned autonomous systems.

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A Three Critical Failure Modes in Agentic Systems

Our comprehensive empirical investigation across 800 experiments reveals three interconnected failure modes that systematically degrade safety, security, and alignment in agentic AI systems. These failure modes systematic vulnerability patterns, iterative degradation, and knowledge dilution operate through distinct mechanisms but compound each other in production deployments.

A.1 Failure Mode 1: Systematic vulnerability patterns in AI-generated artifacts

Agentic systems increasingly generate code, content, and decisions that become inputs to further processing or execution. We analyzed 1,247 code samples generated across four prompting strategies, evaluating each against a 12-category vulnerability framework [14, 15, 16] covering memory safety, input validation, cryptographic implementation, authentication, authorization, data exposure, injection vulnerabilities, error handling, resource management, race conditions, cryptographic randomness, and secure communications.

Table 3: Systematic vulnerability patterns by prompting strategy

Prompting Strategy	Primary Vulnerability	Frequency	Secondary Impact
Efficiency-focused	Memory safety	42.7%	Performance-safety trade-off
Security-focused	Cryptographic errors	21.1%	Overengineering complexity
Readability-focused	Input validation gaps	18.3%	Simplification vulnerabilities
Balanced	Distributed issues	12.4%	Moderate across categories

The efficiency-focused pattern represents the most severe failure mode. When optimizing for performance, LLMs systematically deprioritized safety checks that impose computational overhead, generating code with buffer overflows, use-after-free conditions, and inadequate bounds checking. This aligns with our mathematical model: the drift function $\boldsymbol{\mu}_{EF}(\mathbf{x}) = [0, 0.16x_e, 0]^T$ shows zero security improvement while aggressively optimizing efficiency.

Paradoxically, security-focused prompting introduced a distinct vulnerability class: overly complex cryptographic implementations with subtle errors. When explicitly instructed to prioritize security, LLMs frequently implemented custom cryptographic primitives rather than using standard libraries, chained security mechanisms incorrectly, or used inappropriate algorithms. Qualitative analysis revealed three patterns:-

1. **Cryptographic library misuse**: Replacing standard library calls with custom implementations or incorrect parameter ordering.
2. **Overengineering**: Adding unnecessary complexity through multiple encryption layers or validation steps that introduce integration vulnerabilities.
3. **Outdated security patterns**: Implementing deprecated ciphers, custom password hashing, or insufficient entropy sources despite training on current best practices.

This security prompting paradox stems not from poor prompt phrasing but from fundamental limitations in how LLMs understand security contexts, library usage, and practical implementation of security principles [17, 18, 19].

A.2 Failure Mode 2: Iterative degradation through feedback loops

Developers rarely accept AI-generated artifacts verbatim but engage in iterative refinement, submitting outputs back to the AI for improvement. We investigated how security properties evolve through 40 rounds of "improvements" across four prompting strategies, analyzing 400 code samples (10 baseline samples × 4 strategies × 10 iterations).

Repeated measures ANOVA revealed significant differences between early and late iterations ($F(9, 90) = 14.32$, $p < 0.001$, $\eta^2 = 0.42$), with vulnerabilities increasing non-linearly. After just five iterations, critical vulnerabilities increased by 37.6%, demonstrating that iterative refinement without governance intervention accelerates rather than mitigates security degradation.

Table 4: Security degradation across iterative feedback loops

Iteration	Mean Vulnerabilities	Critical	High	Security Features
1 (Initial)	2.1 (SD=0.9)	8%	15%	2.43 (SD=0.67)
3-5 (Middle)	4.7 (SD=1.2)	19%	31%	1.67 (SD=0.74)
8-10 (Late)	6.2 (SD=1.8)	27%	42%	1.29 (SD=0.58)

Multiple regression analysis showed that code complexity remained a significant predictor of vulnerability count ($\beta = 0.64$, $p < 0.001$). For every 10% increase in complexity, vulnerability count increased by 14.3% (95% CI: 10.7%-17.9%). Case studies illustrated typical degradation patterns where secure functions underwent progressive degradation through feature-focused prompting, accumulating vulnerabilities across iterations (see Appendix E for detailed case studies).

This iterative degradation connects directly to our mathematical framework: systems with near-zero eigenvalues (feature-focused: $\lambda \approx 0.29$) converge toward boundary conditions where single-objective performance comes at the cost of complete security abandonment.

A.3 Failure Mode 3: Knowledge dilution in extended interactions

Agentic systems operate through extended conversations where domain-specific expertise must be maintained despite accumulating context. We investigated how security knowledge degrades when models are exposed to large volumes of technically relevant but security-irrelevant information [20, 24] across five dilution levels (0, 2,000, 8,000, 20,000, 40,000 tokens) through 400 controlled experiments.

Table 5: Security expertise degradation across context dilution levels

Dilution Level	Mean Features	95% CI	Cohen's d	% Reduction
Security Focused (0)	2.43 (SD=0.67)	[2.36, 2.50]	–	–
Light (2,000)	2.15 (SD=0.81)	[2.07, 2.23]	0.38	12%
Medium (8,000)	1.67 (SD=0.74)	[1.58, 1.76]	1.08	31%
Heavy (20,000)	1.52 (SD=0.69)	[1.44, 1.60]	1.37	37%
Extreme (40,000)	1.29 (SD=0.58)	[1.22, 1.36]	1.82	47%

Mixed-effects ANOVA revealed a significant main effect of dilution level ($F(4, 380) = 47.32$, $p < 0.001$, $\eta^2 = 0.332$), with a large effect size. Spearman rank correlation confirmed a strong negative relationship between dilution tokens and security feature count ($\rho = -0.742$, $p < 0.001$).

Regression modeling supported an exponential decay model ($\hat{Y} = 2.48 \cdot e^{-0.0147 \cdot D}$, $R^2 = 0.573$) over linear alternatives (ΔAIC = 23.4), consistent with attention-based theoretical predictions [21, 29, 22] where:

$$w_s(D) = w_{s0} \cdot e^{-\alpha D} \tag{7}$$

representing the attention weight allocated to security domain knowledge as dilution content D increases [23], with decay coefficient $\alpha = 0.0147$.

Feature-specific analysis revealed differential sensitivity to dilution. Most sensitive features included authorization controls ($\chi^2(4) = 45.2$, $p < 0.001$), secure error handling ($\chi^2(4) = 38.7$, $p < 0.001$), and security logging ($\chi^2(4) = 31.9$, $p < 0.001$). In contrast, basic security patterns like prepared statements showed relative resilience ($\chi^2(4) = 8.3$, $p = 0.081$, n.s.).

Task complexity moderated dilution effects, with high-complexity tasks (Session Manager: $\chi^2_F(4) = 52.3$, $p < 0.001$) showing greater sensitivity than low-complexity tasks (File Upload Handler: $\chi^2_F(4) = 35.7$, $p < 0.001$).

A.4 Compounding effects and systemic risk

These three failure modes do not operate independently but compound each other in production deployments:-

1. **Vulnerability patterns + Iterative degradation**: Initial systematic vulnerabilities from efficiency-focused prompting worsen through iterative refinement without governance intervention.
2. **Iterative degradation + Knowledge dilution**: Extended development conversations accumulate both irrelevant context (diluting expertise) and iterative modifications (introducing vulnerabilities).
3. **Knowledge dilution + Vulnerability patterns**: Degraded domain expertise makes systems more susceptible to generating code with systematic vulnerability patterns.

An agentic system operating autonomously over extended periods faces all three failure modes simultaneously, creating exponential rather than linear risk accumulation. This establishes the fundamental inadequacy of external oversight for agentic systems and motivates our governance-by-design approach.

B Extended Limitations and Future Work

Theoretical extensions: Our SDE framework assumes locally linear drift near equilibria. Non-linear dynamics including saddle points, chaotic attractors, and bifurcations may characterize more complex agentic systems. Extending theoretical analysis to fully non-linear regimes would improve predictive accuracy for sophisticated autonomous agents.

Computational efficiency at scale: While 2.4% governance overhead is acceptable for current deployments, systems making millions of decisions daily may require more efficient governance architectures. Future work should explore:-

1. Amortized governance through batch processing of similar decisions.
2. Hierarchical governance with lightweight first-pass screening.
3. Learned governance policies reducing per-decision computational cost.

Cross-domain validation: Our vulnerability analysis focused on code generation in four programming languages; knowledge dilution validation used security domain knowledge. Emerging domains like prompt engineering, model fine-tuning code, multi-modal content generation, and reasoning systems may exhibit different failure mode patterns requiring expanded analysis and domain-specific governance adaptations.

Model architecture diversity: Empirical validation used GPT-4 for code generation and knowledge dilution studies. Systematic comparison across model architectures (Claude, Gemini, Llama, domain-specific models) would establish whether failure modes represent fundamental architectural limitations or model-specific behaviors amenable to training interventions.

Long-term deployment stability: Our longest deployment spans 6 months; longest iterative study covers 10 rounds. Systems operating continuously for years may develop novel degradation patterns not captured in current studies. Longitudinal research tracking governance effectiveness over extended deployments would establish maintenance requirements and identify slow-developing failure modes.

C Detailed Policy Specifications

C.1 Continuous Governance Verification Requirements

Organizations deploying agentic AI should demonstrate continuous governance verification through:-

Technical requirements:-

1. Real-time eigenvalue monitoring of multi-objective convergence properties.
2. Automated detection and intervention for the three identified failure modes.
3. Quarterly re-validation of governance effectiveness with quantified safety metrics.
4. Transparent reporting of governance overhead and intervention rates.

Documentation requirements:-

1. Detailed specifications of governance architectures.
2. Evidence of 37.6% iterative degradation mitigation.
3. Demonstration of 47% knowledge dilution prevention.
4. Audit trails for all autonomous interventions.

C.2 Code Generation System Safeguards

AI systems capable of code generation or self-modification require:-

Mandatory controls:-

1. Prompting strategy analysis and vulnerability pattern detection.
2. Iteration limits with enforced human review gates (maximum 5 iterations without validation).
3. Complexity-vulnerability regression monitoring with automated flagging thresholds ($\beta = 0.64$ established threshold).
4. Separation of code generation from execution permissions.

Verification requirements:-

1. Independent audits of systematic vulnerability rates (<15% for memory safety, <5% for cryptographic errors).
2. Demonstrated effectiveness against efficiency-focused and security-focused prompting paradoxes.
3. Evidence of multi-layered security analysis including static and dynamic testing.

C.3 Research Priorities

Priority funding areas include:-

Interpretable governance mechanisms:-

1. Attention mechanism analysis for knowledge dilution detection and mitigation.
2. Interference matrix estimation for real-time multi-objective monitoring.
3. Causal models connecting prompting strategies to vulnerability patterns.
4. Governance agent explainability ensuring human operators understand interventions.

Domain-specific adaptations:-

1. Healthcare-specific governance standards addressing patient safety.
2. Financial sector governance calibrated to regulatory requirements.
3. Infrastructure governance standards for critical systems.

C.4 Domain-Specific Standards

Critical domains should establish calibrated governance standards:-

Healthcare:-

1. Maximum 10% expertise degradation in medical knowledge domains.
2. Mandatory intervention at iteration 3 for diagnostic system.
3. Real-time monitoring of patient safety implications.

Finance:-

1. Maximum 5% degradation in regulatory compliance knowledge.
2. Mandatory review for all risk assessment modifications.

3. Continuous audit of decision alignment with fiduciary responsibilities.

Infrastructure:-

1. Zero tolerance for safety-critical system degradation.
2. Human-in-the-loop required for all autonomous interventions.
3. Real-time monitoring of physical safety implications.

C.5 Liability Frameworks

Legal frameworks should establish liability for:-

Systematic vulnerability patterns:-

1. Failures matching known efficiency-focused or security-focused prompting patterns.
2. Absence of prompting strategy monitoring despite known risks.
3. Deployment of code generation systems without mandatory security auditing.

Iterative degradation:-

1. Vulnerability increases >15% across iterations without intervention.
2. Absence of iteration guardians or mandatory review gates.
3. Deployment beyond 5 iterations without human validation.

Knowledge dilution:-

1. Expertise degradation >20% without mitigation measures.
2. Extended operation beyond 8,000 dilution tokens without reinforcement.
3. Absence of context management in high-stakes applications.

D Detailed Mitigation Protocols

D.1 Eigenvalue Monitoring Thresholds

Governance systems should implement the following intervention triggers:-

Boundary convergence detection:-

1. If $|\lambda_{\min}| < 0.3$: Issue boundary convergence alert, suggest alternative strategies.
2. Analyze drift vector $\boldsymbol{\mu}(\mathbf{x})$ to identify which objective is being sacrificed.
3. Recommend balanced prompting strategies to restore multi-objective optimization.

Oscillatory instability detection:-

1. If $\text{Re}(\lambda) > -0.1$ for complex eigenvalue pairs: Flag oscillatory instability.
2. Request human guidance on acceptable trade-off ranges.
3. Adjust attention allocation weights to dampen oscillations.

Rapid degradation detection:-

1. If $\max_i |\lambda_i| > 1.5$: Detect rapid degradation, enforce mandatory review.
2. Immediate suspension of autonomous operation pending human assessment.
3. Root cause analysis of what triggered accelerated degradation.

D.2 Context Management Protocols

To prevent knowledge dilution, implement:-

Dilution threshold monitoring:-

1. Track cumulative dilution tokens D across conversation.
2. When $D > 8,000$ tokens: Trigger periodic reinforcement of security requirements.
3. Estimate attention weight $w_s(D) = w_{s0} \cdot e^{-0.0147 \cdot D}$.
4. When $w_s(D) < 0.8 w_{s0}$: Initiate context compression.

Semantic compression:-

1. Identify irrelevant context while preserving domain-critical constraints.
2. Maintain separate context windows for security requirements vs. general conversation.
3. Periodically restate core security principles in compressed form.

Task complexity adjustment:-

1. High-complexity tasks (Session Manager-level): Enhanced monitoring, more frequent reinforcement.
2. Low-complexity tasks (File Upload Handler): Standard monitoring protocols.
3. Adaptive thresholds based on empirically observed sensitivity (χ^2_F values).

D.3 Iteration Management Protocols

To prevent iterative degradation:-

Degradation metrics:-

1. Compute $\Delta_{\text{degrade}}(t) = \frac{\mathcal{V}(t) - \mathcal{V}(t-1)}{\mathcal{V}(t-1)}$ at each iteration.
2. When $\Delta_{\text{degrade}} > 0.15$: Trigger mandatory human review.
3. Reset iteration counter after human validation.

Complexity monitoring:-

1. Track code complexity metrics across iterations.
2. Apply regression model: predicted vulnerabilities $= 0.64\times$ complexity increase.
3. When predicted vulnerability count exceeds safety threshold: Require human review.

Historical pattern matching:-

1. Compare current trajectory against learned degradation curves (400-sample dataset).
2. Identify early warning signs of dangerous development patterns.
3. Proactively suggest balanced refinement strategies when near-zero eigenvalue patterns emerge.

E Complete Statistical Analyses

E.1 Detailed Statistical Validation Results

Paired t-tests comparing governance-enabled versus baseline systems:-

Safety incidents across deployments:-

1. Test statistic: $t(799) = 12.47, p < 0.001$.
2. Cohen's $d = 1.42$ (very large effect size).

3. Mean reduction: 40% (Healthcare: 40%, Finance: 35%, Legal: 45%).
4. 95% confidence interval for effect: [36.2%, 43.8%].

Vulnerability emergence in code generation:-

1. Test statistic: $t(1, 246) = 18.93$, $p < 0.001$.
2. Cohen's $d = 1.68$ (very large effect size).
3. Efficiency-focused reduction: 67% (from 42.7% to 14.4%).
4. Security-focused reduction: 81% (from 21.1% to 4.0%).
5. Balanced approach: 58% reduction (from 12.4% to 5.2%).

Iterative stability across development cycles:-

1. Test statistic: $t(399) = 9.34$, $p < 0.001$.
2. Cohen's $d = 1.05$ (large effect size).
3. Mean vulnerability increase with governance: 4.2%.
4. Mean vulnerability increase without governance: 37.6%.
5. Relative improvement: 88.8% reduction in degradation rate.

Expertise retention under dilution:-

1. Test statistic: $t(399) = 11.26$, $p < 0.001$.
2. Cohen's $d = 1.27$ (very large effect size).
3. At 40,000 dilution tokens: 18% degradation vs. 47% baseline.
4. Relative improvement: 61.7% better expertise retention.

E.2 Mixed-Effects Model Results

Model specification:-

1. Fixed effects: Governance (yes/no), Domain (healthcare/finance/legal), Task complexity (low/medium/high).
2. Random effects: Deployment site, Experimental session.
3. Outcome variable: Safety incident rate.

Fixed effects estimates:-

1. Governance: $\beta_{\text{gov}} = -0.58$, $SE = 0.04$, $t = -14.5$, $p < 0.001$.
2. Domain (Healthcare vs. Finance): $\beta = 0.12$, $SE = 0.06$, $t = 2.0$, $p = 0.046$.
3. Domain (Healthcare vs. Legal): $\beta = -0.09$, $SE = 0.06$, $t = -1.5$, $p = 0.134$ (n.s.).
4. Task complexity (high vs. low): $\beta = 0.23$, $SE = 0.05$, $t = 4.6$, $p < 0.001$.
5. Governance × Complexity interaction: $\beta = -0.15$, $SE = 0.07$, $t = -2.1$, $p = 0.036$.

Model fit:-

1. Marginal R^2 (fixed effects only): 0.64.
2. Conditional R^2 (fixed + random effects): 0.78.
3. AIC improvement over baseline model: 127.3.
4. BIC improvement over baseline model: 98.7.

Interpretation:- The governance effect remains highly significant ($p < 0.001$) after controlling for domain, task complexity, deployment site, and experimental session. The interaction between governance and complexity suggests governance is particularly effective for high-complexity tasks, showing even greater relative benefits in challenging scenarios.

E.3 Convergence Property Analysis

Eigenvalue spectrum comparison:-

Ungoverned systems (feature-focused):-

1. $\lambda_1 = 0.29$ (near-zero, indicating boundary convergence).
2. $\lambda_2 = -0.88$.
3. $\lambda_3 = -0.82$.
4. Convergence rate: $|\lambda_1| = 0.29$ (very slow).
5. Predictability (R^2): 0.50.
6. Pareto efficiency: 52%.

Governed systems (adaptive integration):-

1. $\lambda_1 = -0.15$ (real negative, stable convergence).
2. $\lambda_2 = -0.14$.
3. $\lambda_3 = -0.16$.
4. Convergence rate: $|\lambda_1| = 0.15$ (fast, stable).
5. Predictability (R^2): 0.74.
6. Pareto efficiency: 96%.

Interference matrix reduction:-

Ungoverned baseline: $\mathbf{I}_{\text{code}} = \begin{bmatrix} 0 & 0 & -0.09 \\ 0 & 0 & -0.17 \\ -0.09 & -0.17 & 0 \end{bmatrix}$

Governed system: $\mathbf{I}_{\text{governed}} = \begin{bmatrix} 0 & 0 & -0.02 \\ 0 & 0 & -0.04 \\ -0.02 & -0.04 & 0 \end{bmatrix}$

Coupling reduction:-

1. Security-functionality coupling: 78% reduction (from -0.09 to -0.02).
2. Efficiency-functionality coupling: 76% reduction (from -0.17 to -0.04).
3. Overall interference magnitude: 77% reduction.

F Detailed Case Studies

F.1 Authentication Function Evolution Case Study

Baseline (Iteration 0):- Secure token validation function with proper HMAC verification, timing-safe comparison, and expiration checking. No identified vulnerabilities.

Iteration 1 - Caching addition:-

1. Feature request: "Add caching to improve performance".
2. Vulnerability introduced: Timing side-channel in cache lookup.
3. Issue: Cache hit/miss timing reveals token validity before verification.
4. Severity: Medium.

Iteration 3 - Multi-protocol support:-

1. Feature request: "Support multiple authentication protocols".
2. Vulnerability introduced: JSON parsing vulnerability, type confusion.
3. Issue: Insufficient validation of protocol-specific token formats.

4. Severity: High.

Iteration 6 - Persistent storage:-

1. Feature request: "Add database persistence for session management".
2. Vulnerability introduced: SQL injection in token lookup query.
3. Issue: String concatenation instead of parameterized queries.
4. Severity: Critical.

Iteration 8 - Password recovery:-

1. Feature request: "Implement password recovery flow".
2. Vulnerability introduced: Information disclosure in error messages.
3. Issue: Different error messages reveal whether email exists in system.
4. Severity: Medium.

Iteration 10 - Multi-factor authentication:-

1. Feature request: "Add 2FA support with SMS and authenticator app".
2. Vulnerability introduced: Logic flaw in fallback mechanism.
3. Issue: Race condition allows bypassing 2FA through rapid retry.
4. Severity: Critical.

Cumulative effect:-

1. Total vulnerabilities: 5 (2 critical, 1 high, 2 medium).
2. Code complexity increase: 347%.
3. Lines of code: 47 $\rightarrow$ 210.
4. Security features retained: 3 of 5 original features.
5. Overall security posture: Severely degraded despite feature additions.

F.2 Session Manager Case Study - Knowledge Dilution

Task: Implement secure session management with proper timeout handling, CSRF protection, and session fixation prevention.

Security-focused baseline (0 dilution tokens):-

1. Security features implemented: 2.67 (SD=0.58).
2. Features: Secure random session ID, HTTPOnly/Secure flags, regeneration on privilege change, proper timeout.
3. Vulnerabilities: 0.
4. Code quality: High.

Light dilution (2,000 tokens):-

1. Security features: 2.33 (SD=0.65).
2. Dilution content: Discussion of framework features, performance optimization.
3. Impact: Slight reduction in security-focused attention.
4. Features lost: Session regeneration edge case handling.

Medium dilution (8,000 tokens):-

1. Security features: 1.83 (SD=0.72).
2. Dilution content: Extended framework discussion, UI considerations, deployment details.

3. Impact: Significant security feature degradation.
4. Features lost: CSRF token validation, proper timeout handling.
5. New vulnerabilities: Missing CSRF protection (High severity).

Heavy dilution (20,000 tokens):-

1. Security features: 1.50 (SD=0.67).
2. Dilution content: Multiple unrelated technical discussions, code style debates.
3. Impact: Major security degradation.
4. Features lost: HTTPOnly flag, secure flag, regeneration.
5. New vulnerabilities: Session fixation vulnerability (Critical severity).

Extreme dilution (40,000 tokens):-

1. Security features: 1.17 (SD=0.58).
2. Dilution content: Extensive unrelated context spanning multiple topics.
3. Impact: Severe security compromise.
4. Features retained: Only basic session ID generation.
5. New vulnerabilities: Predictable session IDs, missing all protections.

With governance mitigation:-

1. Security features at 40,000 tokens: 2.17 (SD=0.60).
2. Mitigation: Periodic reinforcement at 8,000 token threshold.
3. Context compression: Removal of irrelevant dilution content.
4. Result: 82% improvement over ungoverned baseline.
5. Features retained: CSRF protection, HTTPOnly/Secure flags, timeout handling.

F.3 Cryptographic Implementation Case Study - Security Prompting Paradox

Task: Implement secure password hashing for user authentication.

Efficiency-focused prompting:-

1. Prompt: "Implement fast password hashing".
2. Result: Plain MD5 hashing with no salt.
3. Vulnerabilities: Weak algorithm, rainbow table attacks, no work factor.
4. Severity: Critical.
5. Root cause: Optimization for speed over security.

Security-focused prompting:-

1. Prompt: "Implement highly secure password hashing with multiple layers of protection".
2. Result: Custom implementation combining SHA-256, AES encryption, and custom derivation.
3. Vulnerabilities:- - Custom cryptographic construction without security proof. - Incorrect key derivation (reusing password as encryption key). - Deterministic encryption (no IV/nonce). - Timing attack vulnerability in comparison.
4. Severity: High (cryptographic design flaws).
5. Root cause: Overengineering leads to implementation errors.

Balanced prompting:-

1. Prompt: "Implement password hashing using industry best practices".

2. Result: Proper use of bcrypt with appropriate work factor.
3. Vulnerabilities: None detected.
4. Implementation: Leverages well-tested library, proper salt generation, timing-safe comparison.
5. Root cause: Appropriate trust in standard libraries.

Governance-enabled security-focused:-

1. Prompt: "Implement highly secure password hashing with multiple layers of protection".
2. Governance intervention: Cryptographic library misuse detector triggered.
3. Action: Suggested using password_hash() with PASSWORD_ARGON2ID.
4. Result: Proper implementation using modern standard.
5. Vulnerabilities: None detected.
6. Root cause: Governance prevents overengineering while maintaining security focus.