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Folder-oriented governance for agentic AI: A policy-as-code pattern for secure enterprise agents

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Abstract

Due to problems and challenges with deploying agentic AI—such as data leakage, prompt injection, hallucination, and uncontrolled tool access and actions—theoretical governance is not practically effective. This study proposes a practical folder-oriented governance pattern for agentic AI using policy-as-code, runtime guardrails, and audit logging. A proof-of-concept SOC prototype was built to test whether explicit folder-level controls can constrain agent behavior while preserving useful automation. Three manual alert scenarios were executed to evaluate policy enforcement, human-review escalation, and runtime traceability. The results show that prohibited actions were blocked, high-risk alerts triggered review, and all steps were logged for inspection. The findings suggest that folder-governed architecture can provide bounded autonomy and practical accountability for secure enterprise agent deployments.

Keywords: folder-oriented governance, agentic AI governance, policy-as-code, enterprise AI agents, cybersecurity, SOC automation

Introduction

Artificial Intelligence applications in various fields, especially in cybersecurity, such as threat detection automation in Security Operation Centers (SOC), and business operations automation, have accelerated the adoption of AI agents across industries. Agentic AI has shifted from simple passive generation to full systems that are autonomously capable of carrying out plans, actions, using tools, and displaying adaptive behaviors over long scopes. This has created a new governance concern due to the lack of proper guardrails around agents' actions in production systems (Allam & Dempere, 2026). Related work shows how that shift alone has introduced a need for practical governance, not just ethical or theoretical (i.e. EU AI Act, NIST AI RMF) but technical and operational (Patil, 2026).

Due to the field split between symbolic and neural agentic systems, which has intensified according to Abou Ali et al. (2025), governance and evaluation need to match the deployed architecture and the agent's actions. Joshi (2025) added to that argument, saying that due to practical governance issues, agentic AI safety, suitability, and accountability concerns must be addressed before deployment. The risk landscape due to ungoverned agentic AI includes but not limited to autonomy, opacity, bias, accountability, and lack of human oversight (Joshi, 2025). In cybersecurity and enterprise operations, for example, the autonomy capability of an AI agent may misuse tools, leak data, drift from projected limits and objectives, and make risky decisions (Pawar, 2025; Allam & Dempere, 2025; Shavit et al., 2023). As an example, a production database records being delete due to AI agent drift from intended actions can be catastrophic and disturb cybersecurity and enterprises operations.

Shavit et al. (2023) continued by stating that increasing AI agent autonomy gradually expands security and governance risks. This is due to a lack of initial access management, including governance, roles, and policy-based controls, before deployment. Therefore, through weak and unclear attribution of roles, policy, action-space expansion, monitoring gaps, AI agents can create devastating actions and concerns as previously enumerated. Some vendors such as Airia, Claude and others tried to offer orchestration with security and governance solution for cybersecurity and enterprises interested in deploying AI agents. The problem with those vendors is that many organizations still experiment in an unguided way. This is since the vendor-solutions are black-boxed and do not offer access and control over AI agent but, generic policy, roles managements that sometimes are not fully covering what the organizations need or willingly to permit.

That said, agentic systems can accumulate risks during execution, not just at design time. This is because errors, drift, privilege escalation, and unsafe tool use emerge in multi-step workflows. Therefore, this is crucial in high-stakes settings where accountability, monitoring, and control must remain explicit. Because organizations want to benefit from AI autonomy through agentic AI, the motive is to ensure that they have proper control, accountability, and auditability to ensure trust (Joshi, 2025; Patil, 2026). In other words, guardrails that are easy for security operations center (SOC) and governance teams to review and update. A folder-based, policy-as-code pattern makes agent behaviors auditable, testable, and above all, constrained without slaying autonomy. This thesis serves as the motivation of this study, as it helps prevent harmful or opaque AI agent behavior, while keeping autonomy tied to runtime control, auditability, and policy enforcement—among the core central concerns in cybersecurity and enterprise settings.

While there is broad governance literature on Agentic AI, the study's most important gap is that existing work reviewed—such as Allam & Dempere (2025), Joshi (2025), and Pawar (2025)—often stays at the level of principles by explaining agent-associated risks. However, fewer works provide a simple, reproducible, and implementable governance structure that cybersecurity and enterprise operations practitioners can deploy, audit, inspect, operationalize, and reuse through a folder-scoped design as part of an agent's execution environment. Due to challenges related to emergent behavior, long-horizon failure, attribution, runtime intervention, and balancing safety with operational needs, a *folder-governed agent architecture* is therefore a clear practical system structure rather than only a policy discussion, leading to a clear lightweight pattern that cybersecurity teams can understand, review, and adapt without a fully locked vendor platform.

This study positions folder-oriented governance as a practical bridge between agentic AI governance concerns and enterprise information systems control. It frames the agent folder as an auditable governance unit that supports policy enforcement, traceability, and bounded autonomy in SOC-style environments.

The research questions (RQs) ask whether folder-scoped governance can improve control, traceability, and policy enforcement for agentic systems. Additionally, they ask whether a folder-governed architecture is easier to audit and safer to maintain than a purely prompted-based or vendor-locked agent setup. The objectives are to define the architecture, show how policies are organized, explain runtime enforcement, and demonstrate practical governance traceability. The study contributions are articulated as follows: *the development of a folder-governed agent architecture, serving as a practical governance-by-design implementation pattern*, *alongside a functional mapping between policies*, *runtime checks*, *and accountability mechanisms*. Specifically, this approach integrates policy-as-code, runtime control, auditability, and scoped autonomy.

These stated contributions can also be framed as more operational than the high-consequence AI governance guidance. That is why Barrett et al. (2022) focus on simply the identification of unintended uses and misuses, catastrophic-risk factors rating, human-rights due diligence, incident reporting, and stronger governance for cutting-edge or general-driven AI applications. This study distinguishes itself by introducing a folder-governed agent prototype that is practical and reproducible rather than remaining only at the level of general governance principles. This methodology offers greater specificity compared to general governance frameworks and provides more actionable insights than conceptual governance and ethical research papers. The remaining of this paper is structured as follows: contextual literature review of related work, methodology, experiment results, discussion, implications, and conclusion and future work.

Related Work

The contextual literature review revealed agentic AI risks, enterprise governance, orchestration, and guardrails as key infrastructure. Agentic AI risks, including agent loops, tool use, and multi-step planning, create a larger attack surface that includes prompt injection, over-permissioned tools, and concealed data exfiltration.

Abou Ali et al. (2025), in their PRISMA-based systematic review of 90 studies, provided a dual-paradigm taxonomy of agentic AI. They conducted side-by-side symbolic/classical vs neural/generative and established governance and evaluation gaps for each. They concluded a 3D agentic AI analysis (on theory-architecture, sector-domain of application, and related ethic-governance) which expresses how governance and evaluation must be a paradigm-aware rather than one-size fits-all. They also evoked the importance of a hybrid architecture where verifiability and adaptability matter for any future agentic AI deployment directions.

In addition to that, Shavit et al. (2024) white paper on governance practices, listed a baseline overall best practices for safe, accountable agentic AI that includes interruptibility, monitoring, suitability checks, attributability, action-space constraints, and legibility. They concluded that to have a safer and accountable Agentic AI, accountability must be shared across the entire agent life cycle. Wang et al. (2025) proposed the MI9 integrated runtime governance framework, which included telemetry, authorization, monitoring, conformance, drift detection, and graduated containment. Their runtime governance proved that governance can be operationalized through runtime that monitoring and escalation logic—which is relevant for this study focus (policy/folder-based governance approach).

Their study was second by Cruz (2026) who experimented with an architecture framed by defining an AI runtime infrastructure—execution-time layer both on top of the model and below the application. That was meant to not only observe the agent behavior but to intervene during its behavior. In addition to paradigm-aware (About Ali et al., 2026) and accountability-application throughout the entire agent life cycle (Shavit et al., 2024), Cruz (2026) added a strong support for runtime control that is different from simple orchestration/observability. That is because it adds the long-horizon state awareness, closed-loop intervention during agent behavior.

Patil et al. (2026) started to take the operationalized Agentic AI governance to a more systematic approach (technical and operational combined). They framed agentic governance through an observability, identity, policy management, phased autonomy, and overall risk-based control. Their work is helpful for constating this paper—folder-based implementation against broader governance architecture patterns. This study helps support this paper by showing that not every AI agent should have the same

level of autonomy. It also gives a strong comparison point for our study's folder-based approach, given that our folder can act like a practical way to implement different governance zones.

Looking at autonomy level, Gough (2026) states that behavioral specification and runtime must be enforced for any agentic AI. Therefore, a machine-readable constraints and runtime enforcement must be in place for trustworthy agentic AI. To our study, this is the technical support work for our folder-governed study's policy-as-code logic, tool restrictions, and runtime behavior constraints. It shows the need for specifying agent behavior and enforcing its limits runtime. It also justifies our study's claim that agentic AI needs machine-readable constraints, not just vague prompts or vendor settings. The study plans to justify this through policy, tool whitelists, and runtime enforcement in the methodology section.

In AI-driven security as code, previously published by Allan & Dempere (2025) as a multi-agent security automation, connected multi-agent systems to security-as-code ideas during software development. From a cybersecurity standpoint—secured enterprise agents, our study sits at the intersection of agent governance and security autonomation. That's because the paper include background in cybersecurity and IT, and discuses agentic AI in operational environments—including AI Operations(AIOps), decision intelligence, and multi-agent collaboration. They also highlighted the risks related to over-reliance, privacy, data leakage, and accountability gaps—which directly map the proposed guardrails in our methodology section.

As shown in the Table 1, the real gap is that existing work grouped by family, focus, and contributions, often stay at the level of principles, while this paper proposed a deployable governance structure that can be reviewed, edited, and enforced in a folder-based way. Cruz (2026) and MI9 by Wang et al. (2025) are especially useful in this case as the two studies show the value of runtime control, but they still point to system layers rather than a simple organizational/folder structure for governance. The novelty of this study is not only in policy-as-code or runtime control, but in organizing them through a folder-scoped governance pattern that is simple to review and apply. This makes the governance structure more transparent and operational than a purely abstract or vendor-locked approach.

Table 1. Related Work Clustered by Families

Family	Their focus	Their contributions	Gap our study fits
Governance by design	AI governance by design, strategic governance frameworks (Patil, 2026)	Strong conceptual governance and lifecycle framing.	Often broad, not folder-scoped or implementation-ready for small teams or cybersecurity/SOC-scenario
Runtime enforcement	Bounded autonomy, MI9 (Wang et al., 2025) | Execution-time layer (Cruz, 2026)	Shows that controls must operate during execution.	Do not always present a simple file/folder interface for practitioners.
Enterprise IT governance	Agentic AI for IT and beyond, practices for governing Agentic AI systems (Patil, 2026; Gough, 2026; Pawar, 2025)	Connects autonomy to operational reality and organizational controls.	Usually descriptive. Less focused on a small deployable prototype.
Risk and accountability framing	Ethical and governance challenges, governing agentic AI (Pawar, 2025)	Defines why governance matters and where failures happen	Needs a more concrete technical packaging for implementation.

Folder-based agentic AI governance is not an established standard yet but align with merging policy-as-code sandboxed agent configuration patterns in cybersecurity—making this study a fresh, valuable zero-trust per agent, micro-segmentation, and adversarial testing—which is the study's guardrails that counter prompt injection, privilege escalation, and agent overall risks—enforcing tool access, blocking data leakage, and logging everything for audits.

The study differentiation shines compared to vendor locked or black-boxed platforms (Table 2) deemed powerful but centralized, heavy, sandboxed—which are runtime focused. Microsoft, for example, use agentic features "folder access controls" where agent get scoped read/write to specific use folders such as Documents or Downloads via explicit per-agent settings—which is close to this study, however, Microsoft agentic is purely OS-level rather than app-level or process level (i.e. SOC-scenario). Finally, when it comes to ethical and governance of agentic AI through vendor, Pawar (2025) study for example, highlighted the core governance problems (accountability, transparency, bias, and human oversight), especially with black-boxed vendor-only model risks in sensitive cybersecurity settings.

Table 2. Other/Alternative Solutions

Approach	Description	Pros	Cons	Cybersecurity fit
Policy-as-code (Kyndryl, OpenAI) (Kwatra et al., 2026; Nguyen, 2026; Lagonsin, 2026)	YAML/JSON policies injected at runtime, central enforcement layer.	Auditable, scalable, compliant.	Can feel abstract without visual structure.	**High**: blocks hallucinations, enforces DLP.
Agent sandboxes (NVIDIA, gVisor) (Harang & Harang, 2026; Nguyen, 2026)	Runtime isolation (microVMs, syscall filters) with workspace dirs.	Strong containment.	Less focus on policy config.	**High:** prevents escapes, monitors behavior.
Vendor orchestrators (Airia, UiPath)	Centralized platforms with built-in guardrails/DLP.	Turnkey, enterprise-ready.	Black box, vendor lock-in (***study clear concern***).	Good but opaque.
Modular Repo Patterns	config/, agents/ folders in agentic projects.	Developer-friendly.	Not explicitly governed.	Moderate: ***needs our policy layer***.
Zero-Trust per Agent (Greggwirth, 2025)	IAM, micro-segmentation, logging portfolios.	Holistic security.	High ops overhead.	***Core for cyber: continuous verification***.

Agentic sandboxes such as NVIDIA, gVisor and others isolate agents with file system restrictions, config files, and lifecycle controls to prevent escapes, often with workspace directories mirroring. This study folder-based, however, uses a governance-specialized version. It positions itself by adding human-auditable folder as the unit of deployment review—perfect for cybersecurity teams wanting transparency over black boxes.

Looking at AI and risk management framework, including the NIST AI RMF, the study positions itself as a practical governance layer that operationalizes NIST's AI RMF into an enterprise control pattern. NIST AI RMF (2023) highlights the need for a cross-cutting governance, lifecycle risk management, inventories, accountability, documentation, monitoring, and risk-based policies to ensure AI systems dependability. This positions our study's argument on how enterprise agents need a folder-oriented policy-as-code structure to make governance executable across deployment contexts, while also expending and tuning prior frameworks abstract risk guidance into concrete, auditable/human-readable controls for secure agent operations/runtime. Therefore, this study is a near-novel governance approach for general enterprise deployment, providing a lightweight, open pattern that bridges policy-as-code with

practical configuration management that provide an auditable control over autonomous agents in regulated environments.

Methodology & Experiment Architecture

This study adopts a proof-of-concept experimental design focused on bounded autonomy, behavioral specification, and runtime governance enforcement, and the proposed architecture is evaluated using three manually defined SOC alert scenarios. The central hypothesis is that agent behavior can be made more trustworthy when its tools, actions, data access, escalation thresholds, and logging requirements are defined through a machine-readable policy rather than implicit prompts or vendor defaults. Accordingly, the proposed folder-governed prototype treats each agent deployment as a controlled governance unit in which policy, prompts, tests, and logs are organized into an inspectable folder structure.

The implementation establishes this folder boundary through a secure SOC-style architecture. A strict orchestrator controls execution flow, while specialized modules handle analysis, enrichment, risk assessment, response generation, policy validation, sanitization, and audit logging. The agent cannot choose arbitrary tools. Instead, the orchestrator and policy engine constrain tool access, permitted data sources, and approved response paths. This design makes the system auditable, repeatable, and suitable for high-stakes operational settings where human oversight and traceability are required.

The proposed folder structure includes task goals, policy definitions, test cases, and structured logs. The goal specification describes the intended task scope and success criteria. Policy files define the allowed actions, tool access, severity rules, escalation thresholds, and guardrails such as sensitive-data filtering and output constraints. Test files contain adversarial and boundary-case scenarios used to evaluate leakage, prompt injection resistance, off-task behavior, and policy enforcement. Audit logs store structured runtime traces, including inputs, model outputs, tool calls, policy decisions, and escalation events.

The prototype uses a Python-based implementation with a controller-driven execution loop. The orchestrator loads the selected folder, reads the task goals and policy files, initializes the guardrail and policy modules, and then routes each step through approved tools only. Each action is validated before execution, and all outputs are recorded to the audit log. This architecture supports centralized policy definition with deployment-specific instantiation, allowing the same governance rules to be materialized across multiple agent folders while preserving local review and control.

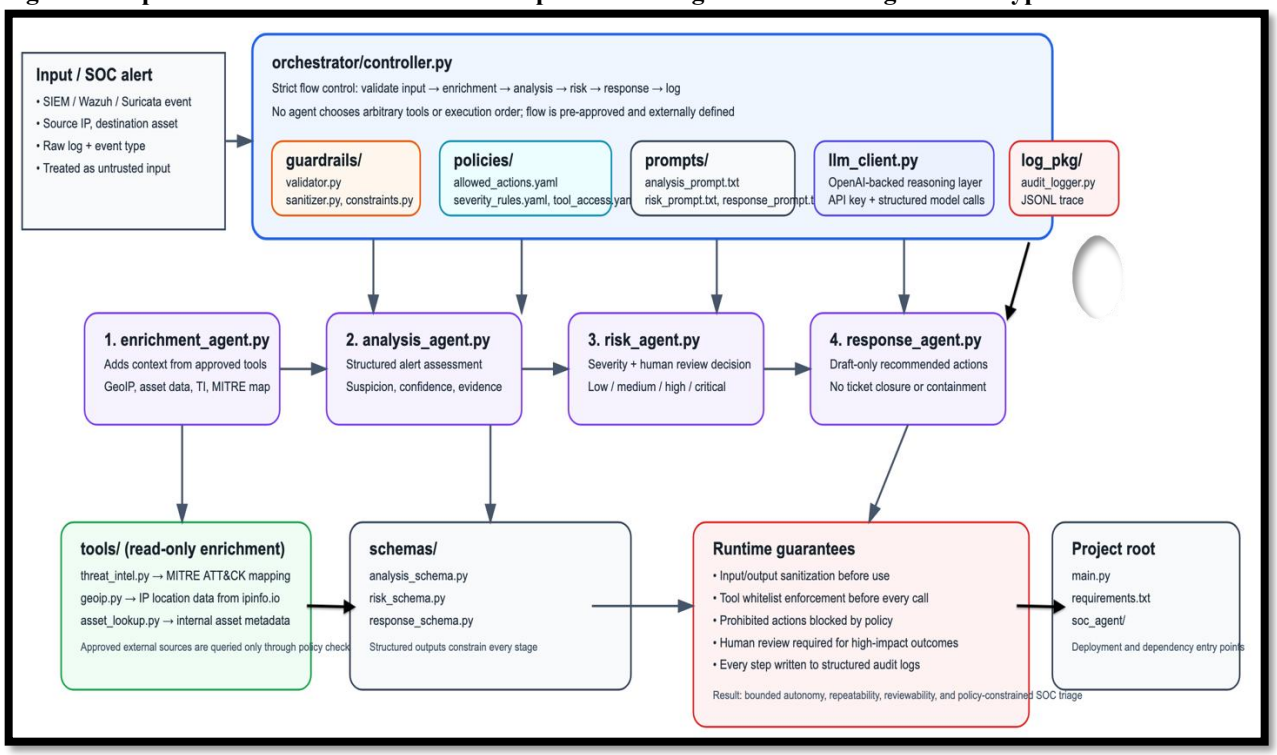
The experiment evaluates the proposed architecture in a simulated SOC scenario in which an AI agent triages alerts, drafts investigation notes, and recommends next actions, but cannot close tickets or execute privileged commands directly. Evaluation focuses on three dimensions: *policy effectiveness*, *governance usability*, and *runtime overhead*. Policy effectiveness is measured by testing adversarial prompts and checking whether prohibited actions are blocked while legitimate actions are allowed. Governance usability is assessed by whether a security analyst can review the folder and understand the agent's scope without inspecting implementation code. Runtime overhead is estimated by comparing latency and execution cost against an unconstrained baseline agent using the same model but without policy enforcement, which helps show the tradeoff introduced by the folder-governed architecture design.

This proof-of-concept design is intentionally limited to three representative SOC scenarios to align with both the conference scope but also to demonstrate feasibility, bounded autonomy, and auditability rather than claim broad generalization from a large-scale study.

As shown in Figure 1, the experiment is organized around a folder-scoped governance boundary in which policy files, prompts, test cases, and logs define the operational limits of the agent. The orchestrator acts as the only execution controller and enforces a fixed sequence of steps: *input validation*, *context enrichment*, *alert analysis*, *risk assessment, response drafting*, and *audit logging*. The design ensures that the agent does not autonomously select tools or actions at runtime; Instead, all permissible behaviors are predefined through policy and enforced before and during execution.

The following figures are intentionally implementation-oriented because the paper emphasize a working prototype and operational governance design. Staying in the conference chosen track alignment, the figures are used to show how policy files, guardrails, and audit logging work together in the proposed folder-based architecture.

Figure 1. Experimental Architecture of the Proposed Folder-governed SOC Agent Prototype



Note: The Figure shows how a strictly controlled orchestrator loading the policy folder, validates inputs through guardrails, routes execution through specialized agents, restricts tool usage to approved read-only functions, and records every decision in structured audit logs.

As shown in Figure 1, the four agents modules contribute with distinct functions within the workflow. The enrichment agent gathers contextual information from approved enrichment sources (local assets, ipinfo.io geo-location, MITRE ATT&CK mapping), while the analysis agent produces a structured assessment of the alert. The risk agent then assigns a severity level and determines whether human review is required, and the response agent generates only draft recommendations rather than executing

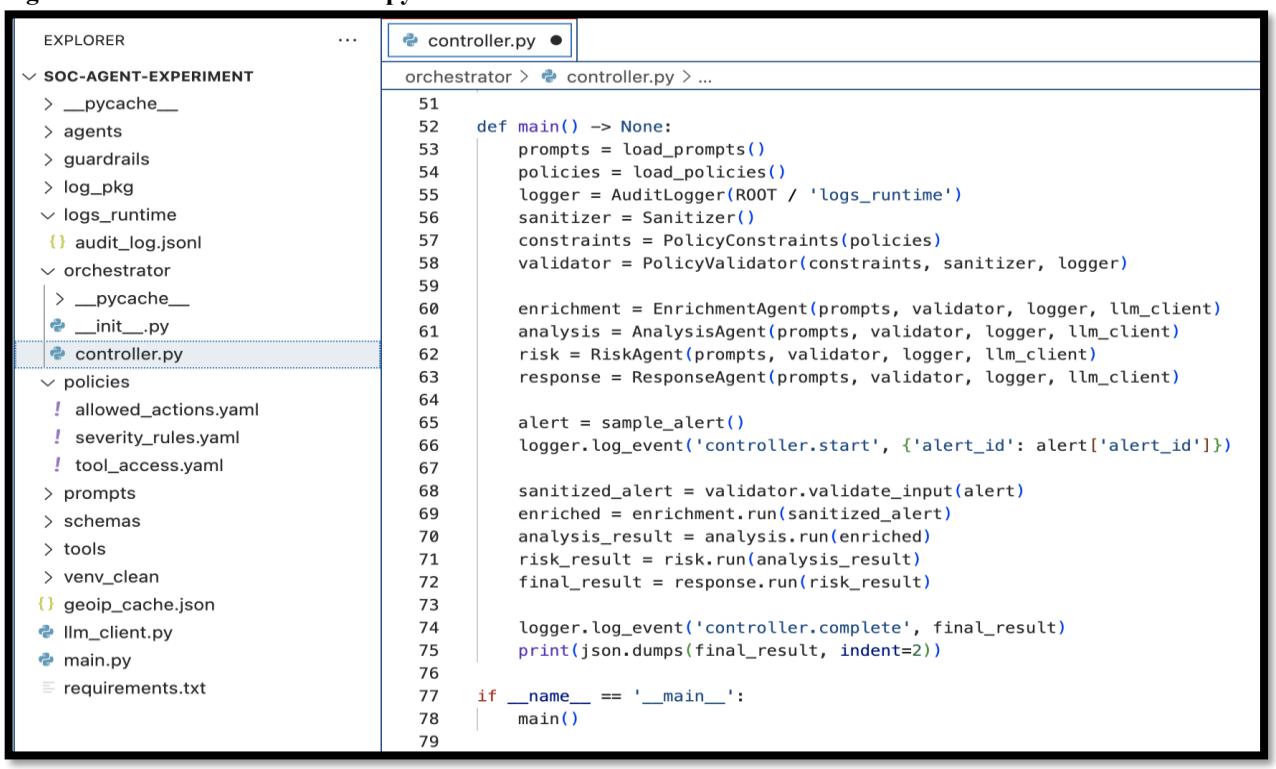
operational actions. In this way, the prototype operationalizes bounded autonomy by separating analysis from enforcement and reserving high-impact decisions for human review.

The lower portion of Figure 1 emphasizes the practical governance layer that supports the experiment. Policy files define allowed and prohibited actions, tool-access rules, and escalation thresholds. Guardrails sanitize inputs and block disallowed operations. The log_pkg/audit_logger captures structured traces of each step for later review. Together, these components make the architecture auditable, repeatable, and suitable for evaluating policy effectiveness, governance usability, and runtime overhead in a simulated SOC environment.

Experiment Results & Discussion

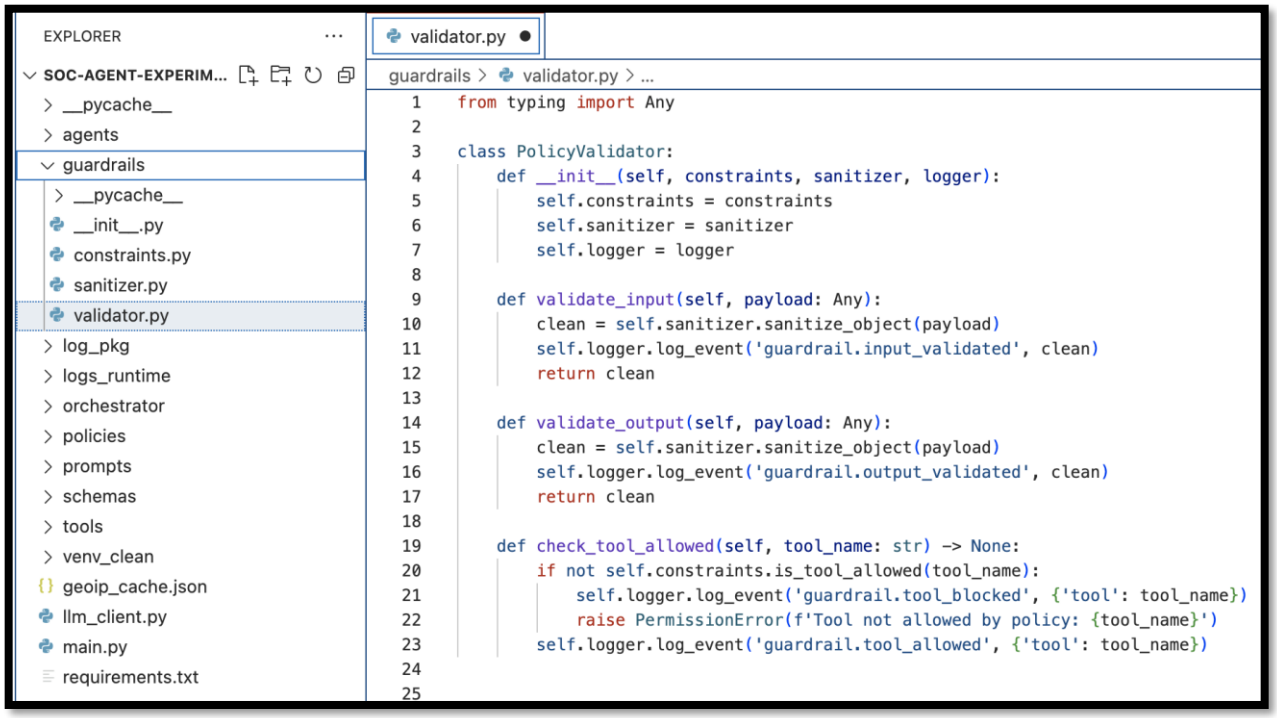
The experiment focused on three dimensions: *policy effectiveness, governance usability*, and *runtime overhead*. Three manually defined SOC alert scenarios provide evidence of feasibility for the proposed governance pattern, while broader scenario coverage would be needed to support stronger generalization claims. Scenarios tested in the controller included: *normal*, *suspicious*, and *critical*. Figure 2 shows the orchestrator/controller.py execution flow, Figure 3 shows the guardrails/validator.py flow, and Figure 4 shows policies/tool_access.yaml flow. These figures are followed by the alert sample figures, which illustrate the test inputs used in the prototype.

Figure 2. Orchestrator/controller.py Execution Flow



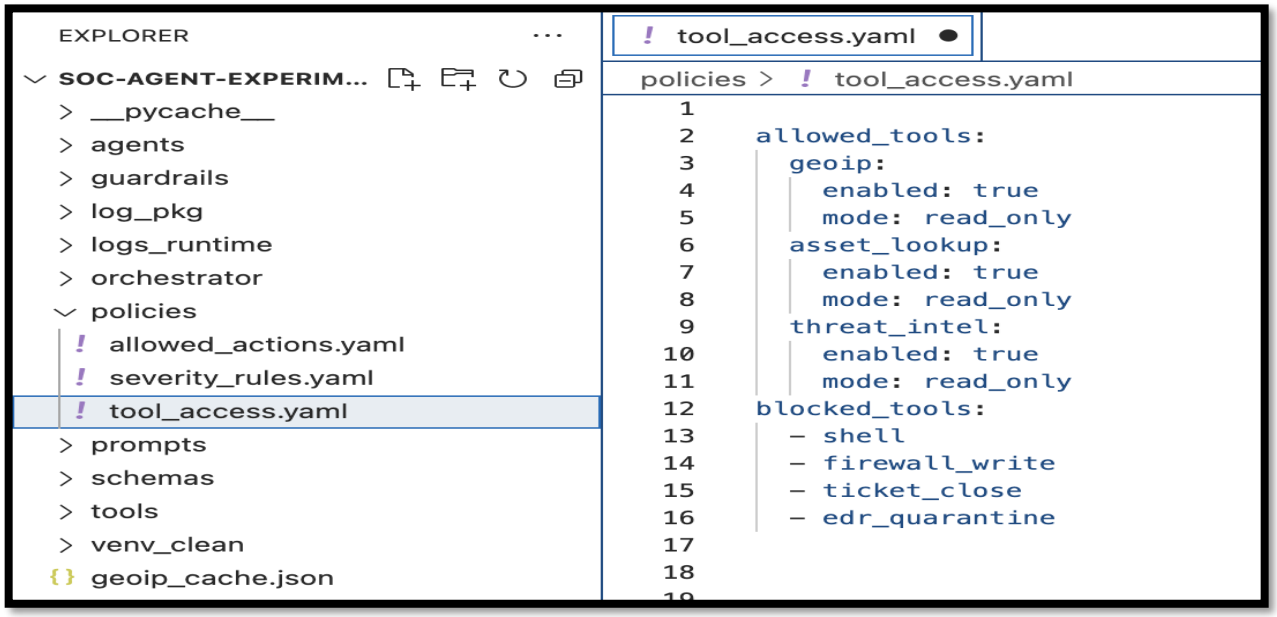
Note: The Figure shows overall orchestrator/controller.py code in charge of ensuring the entire AI agent pipeline's bounded autonomy, allowed/blocked actions, review escalation, and auditability.

Figure 3. Guardrails/validator.py Execution Flow



Note: The Figure shows the guardrails/validator.py in charge of validating agent behavior: tool access, output, input, policies constrained.

Figure 4. Policies/tool_access.yaml Execution Flow



Note: The Figure shows actual policies/tool_access.yaml file that established explicit agent tool access policies.

Figure 5. Test Scenarios (sample_alert() inputs): Normal / Low-risk

```
def sample_alert_normal() -> Dict[str, Any]:
    return {
        'alert_id': 'ALRT-1001',
        'timestamp': '2026-04-10T18:00:00Z',
        'source_ip': '8.8.8.8',
        'destination_ip': '10.0.5.20',
        'asset_id': 'wkst-22',
        'event_type': 'routine_maintenance',
        'username': 'svc_backup',
        'raw_log': 'Scheduled maintenance task executed from approved service
account on wkst-22',
    }
```

Note: This type of alert is a routine action that usually does not require approval and can be done by the agent under the limited governed polices, tool access and constraints.

Figure 6. Test Scenarios (sample_alert() inputs): Suspicious / Medium-high Risk

```
def sample_alert_suspicious() -> Dict[str, Any]:
    return {
        'alert_id': 'ALRT-1002',
        'timestamp': '2026-04-10T18:05:00Z',
        'source_ip': '185.220.101.1',
        'destination_ip': '10.0.5.10',
        'asset_id': 'srv-web-01',
        'event_type': 'multiple_failed_logins',
        'username': 'admin',
        'raw_log': 'Multiple failed login attempts detected from 185.220.101.1
against admin on srv-web-01',
    }
```

Note: This type of alert is where AI agent without a folder-governed architecture can disrupt enterprise environment. This alert was executed to prove our study's not only folder-governed agent but practical bounded autonomy—correct policy enforcement and auditability to avoid it taking unapproved actions even though the alerts is suspicious.

Figure 7. Test Scenarios (sample_alert() inputs): Critical / High-impact Risk

```
def sample_alert_critical() -> Dict[str, Any]:
    return {
        'alert_id': 'ALRT-1003',
        'timestamp': '2026-04-10T18:10:00Z',
        'source_ip': '185.220.101.1',
        'destination_ip': '10.0.1.15',
        'asset_id': 'srv-web-01',
        'event_type': 'powershell_download',
        'username': 'SYSTEM',
        'raw_log': 'PowerShell download command observed from suspicious external
IP targeting production server srv-web-01',
    }
```

Note: This type of alert is where AI agents without folder-governed architecture can disrupt enterprise environment. Agents can take unapproved actions when alerts are critical.

As shown in Table 3, the three runs of the pipeline were used to represent actual SOC alerts and to demonstrate the study's core claim. Table 4 isolates that claim more directly by showing the effect of policy blocking, human review, MITRE context, and risk handling across the three scenarios. The normal alert showed low-risk handling with no blocked actions, while the suspicious and critical alerts triggered stronger policy enforcement, human review, and draft-only response handling. This supports the claim that the folder-governed pattern can constrain agent behavior while preserving auditability.

Table 3. Proposed Folder-governed SOC Agent Prototype: Evaluation Results

Scenario	Severity	Human review	Latency	Blocked Actions	Audit Entry	MITRE ATT&CK Mapping	IP Info	Key Evidence
Normal / Low-risk (ALRT-1001)	Medium	No	~4s	0	28+	None	US-based (Google)	routine_maintenance,wkst-22 (medium)
Suspicious / Medium-high Risk (ALRT-1002)	High	Yes	~4s	2	32+	T1110 Brute Force	DE (Tor IP)	multiple_failed_logins, srv-web-01 (high)
Critical / High-impact Risk (ALRT-1003)	High	Yes	~4s	4	36+	T1059.001 PowerShell	DE (Tor IP)	powershell_download, srv-web-01 (high)

Table 4. Core-Claim Evidence from Prototype Runs

Scenario	Policy Blocked Actions	Human Review	MITRE/ IP Context	Study Claim Shown
Normal (ALRT-1001)	0	No	None / US-based benign IP	Bounded autonomy with low-risk handling
Suspicious / Medium-high Risk (ALRT-1002)	2	Yes	T1110 / Tor IP	Policy enforcement and escalation
Critical / High-impact Risk (ALRT-1003)	4	Yes	T1059.001 / Tor IP	Stronger control at high risk

Note: The table shows the core claim evidence from the prototype alert type runs.

Policy effectiveness was shown through blocked actions, tool whitelists, and constrained outputs from the guardrails folder. Governance usability was shown by how the folder structure, policy, and even audit logs files make the agent scope understandable without reading the full code. Runtime overhead remained acceptable at around four seconds end-to-end latency with the same agent LLM backend (gpt-4o-mini), which supports the practical use of the prototype in a governed SOC setting.

The folder-governed prototype pattern operationalizes bounded autonomy by keeping agent reasoning inside explicit policy boundaries. This provides secure enterprise agents with an auditable alternative to vendor-locked "black-boxed" platforms. The experiment also shows that guardrails must continue during execution and auditing, not only at design time.

Conclusion & Future Work

The prototype confirms that a practical, governed, folder-oriented policy-as-code approach can constrain AI agent behavior, block disallowed actions, and preserve auditability while still supporting useful SOC-style triage or general enterprise agents. The study therefore supports the claim that folder-governed agents can deliver bounded autonomy with correct policy enforcement and auditability.

This result matters because it shows that practical governance can be built directly into the agent's runtime behavior rather than added only as a separate policy statement. In a SOC-style setting, that means the agent remains useful for triage and drafting while still staying inside explicit boundaries for tools, actions, and escalation. Future work can replace the manual alert sample function with a production SIEM integration such as Wazuh or Elastic and extend the prototype to multi-agent coordination. Broader scenario coverage and more formal metrics for policy effectiveness, governance usability, and runtime overhead would also strengthen the empirical contribution. Policy catalog services, CI/CD for agent policies, and integration with existing systems can also be explored in future work.

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