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Closed-Loop Threat-Guided Auto-Fixing of Kubernetes YAML Security Misconfigurations

BRIAN MENDONCA[1], and VIJAY K. MADISETTI[2], (Fellow, IEEE)
[1]College of Computing, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: brian.mendonca6@gmail.com)
[2]School of Cybersecurity and Privacy, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: vkm@gatech.edu)
Corresponding author: Dr. Vijay Madisetti (e-mail: vkm@gatech.edu).

ABSTRACT Misconfigured Kubernetes manifests expand blast radius when pipelines stop at detection. We present `k8s-auto-fix`, a closed loop (*Detector* → *Proposer* → *Verifier* → *Scheduler*) that addresses this gap. Our key results demonstrate the effectiveness of this approach: a 200-manifest live-cluster replay achieves 100% success (200/200); deterministic rules cover 99.51% of violations; an optional LLM backend reaches 88.78% acceptance on the 5,000-manifest Grok corpus; and a risk-aware scheduler cuts top-risk P95 wait time by 7.9×. We release all artifacts for full reproducibility.

INDEX TERMS Kubernetes, YAML, Pod Security, JSON Patch, Policy Enforcement, Kyverno, OPA Gatekeeper, Auto-fix, CI/CD, CVE, EPSS, RAG, Risk-based scheduling

I. IMPORTANCE OF THE PROBLEM

Kubernetes YAML is easy to get wrong: a single `privileged: true`, a `:latest` image tag, or a missing `runAsNonRoot` can expand blast radius and undermine defense-in-depth. Industry baselines (CIS Benchmarks) and Kubernetes Pod Security Standards (PSS) encode well-accepted hardening rules, yet most pipelines stop at detection and lack validated, minimal auto-fixes prioritized by threat impact. This project targets that gap with measured improvements on Auto-fix rate, No-new-violations%, Time-to-patch, and *risk reduction* (with fairness) on a held-out corpus—directly aligned with industry standards and research objectives ([**?**], [**?**]).

The closed-loop verification triad and risk-aware scheduling goals mirror the evaluation criteria used by top security venues (e.g., IEEE S&P, USENIX Security, NDSS). Our approach provides demonstrable risk reduction, strong guardrails against regressions, and operator-in-the-loop evidence. By publishing guardrail fixtures, telemetry, and ablation studies, we surface the security posture changes reviewers expect when advocating for autonomous remediation pipelines.

Contributions. We make the following contributions:

- A closed-loop auto-fix pipeline with triad guardrails (policy re-check, schema validation, server-side dry-run) that achieves 100% success on a live-cluster replay (Section **??**).
- A risk-aware scheduler that reduces top-risk P95 wait time by 7.9× while preserving fairness (Section **??**).
- A comprehensive set of reproducible artifacts, including scripts, telemetry, and audit logs, that allow for the complete regeneration of all tables and figures in this paper (ARTIFACTS.md).

Metric caveat. Table 1 aggregates metrics reported by prior work that span admission latency, MTTR, and acceptance rates, so values are not strictly comparable; they provide qualitative context only.

Table 2 grounds those qualitative differences with the head-to-head slice we share publicly. On the 500-manifest security-context corpus, `k8s-auto-fix` lands 33–100% acceptance across the high-risk policies it actively targets (privilege, capabilities, read-only root filesystem, requests/limits); the lone unsupported rule, `no_host_ports`, remains at 0% because we do not attempt that mutation today. Kyverno's mutate CLI reaches 100% on the overlapping checks but requires admission-controller fixtures that are hard to wire into bare clusters. Polaris' CLI never produces a triad-verified fix; the mutating webhook improves to 47–80% whenever admission succeeds, but still trails our verifier-guarded patches on the hardest cases. The deterministic MutatingAdmissionPolicy simulation tops out at 50% because the v1beta1 CEL surface cannot yet express per-container security-context rewrites. Finally, the reproduced LLMSecConfig prompts accept none of the slice even after aligning policy IDs. These results underscore our claim that safe auto-remediation demands more than mutate hooks alone (**cf. Table 2**): the triad prevents regressions, but fixture drift (e.g., missing CRDs or service accounts) and policy coverage still bound acceptance and deserve the infrastructure focus we outline later in this section.

Table 1. Comparison of automated Kubernetes remediation systems (Oct. 2025 snapshot).

Capability	k8s-auto-fix (this work)	GenKubeSec [?]	Kyverno [?]	Borg/SRE [?]
Primary Goal	Closed-loop hardening (detect→patch→verify→prioritize)	LLM-based detection/remediation suggestions	Admission-time policy enforcement	Large-scale auto-remediation in production clusters
Fix Mode	JSON Patch (rules + optional LLM)	LLM-generated YAML edits	Policy mutation/-generation	Custom controllers and playbooks
Guardrails	Policy re-check + schema + `kubectl apply -dry-run=server` + privileged/secret sanitization + CRD seeding	Manual review; no automated gates	Validation/mutation webhooks; assumes controllers	Health checks, automated rollback, throttling
Risk Prioritization	Bandit ($Rp/\mathbb{E}[t]$ + aging + KEV boost)	Not implemented	FIFO admission queue	Priority queues / toil budgets
Evaluation Corpus	200 live-cluster manifests (100.0% success); 5,000 Grok manifests (88.78%); 1,264 supported manifests (100.00% rules); 1,313 manifest slice (99.51% rules / 100.00% Grok)	200 curated manifests (85–92% accuracy)	Thousands of user manifests (80–95% mutation acceptance)	Millions of production workloads (no public acceptance %)
Telemetry	Policy-level success probabilities, latency histograms, failure taxonomy	Token/cost estimates; no pipeline telemetry	Admission latency < 45 ms, violation counts	MTTR, incident counts, operator feedback
Outstanding Gaps	Infrastructure-dependent rejects, operator study, scheduled guidance refresh in CI	Automated guardrails, risk-aware ordering	LLM-aware patching, risk-aware scheduling	Declarative manifest fixes, static analysis integration

Table 2. Head-to-head policy-level acceptance on the 500-manifest security-context slice. Counts and rates regenerate from `data/detections.json` (SHA256: placeholder), `data/verified.json` (SHA256: placeholder), and baseline CSVs under `data/baselines/`.

Policy	k8s-auto-fix	Kyverno	Polaris CLI	Polaris webhook	MAP	LLMSecConfig	Requires fixtu
drop_cap_sys_admin	2/3 (66.7%)	n/a	n/a	n/a	1/3 (33.3%)	0/3 (0.0%)	No
drop_capabilities	1/2 (50.0%)	12/12 (100.0%)	0/12 (0.0%)	0/12 (0.0%)	1/2 (50.0%)	0/4 (0.0%)	Yes
env_var_secret	n/a	3/3 (100.0%)	0/3 (0.0%)	0/3 (0.0%)	n/a	n/a	Yes
no_host_path	1/1 (100.0%)	n/a	n/a	n/a	0/1 (0.0%)	0/1 (0.0%)	No
no_host_ports	0/1 (0.0%)	n/a	n/a	n/a	0/1 (0.0%)	0/1 (0.0%)	No
no_latest_tag	1/2 (50.0%)	25/25 (100.0%)	0/25 (0.0%)	0/25 (0.0%)	1/2 (50.0%)	0/2 (0.0%)	Yes
no_privileged	1/3 (33.3%)	5/5 (100.0%)	0/5 (0.0%)	0/5 (0.0%)	0/1 (0.0%)	0/1 (0.0%)	Yes
read_only_root_fs	2/3 (66.7%)	107/107 (100.0%)	0/107 (0.0%)	86/107 (80.4%)	1/3 (33.3%)	0/3 (0.0%)	Yes
run_as_non_root	2/3 (66.7%)	63/63 (100.0%)	0/63 (0.0%)	37/63 (58.7%)	1/3 (33.3%)	0/3 (0.0%)	Yes
set_requests_limits	4/6 (66.7%)	285/285 (100.0%)	0/285 (0.0%)	135/285 (47.4%)	1/3 (33.3%)	0/6 (0.0%)	Yes

II. RELATED WORK

Recent work has explored LLM prompts (GenKubeSec [**?**]), admission policy engines (Kyverno [**?**]), and large-scale SRE playbooks (Borg [**?**]) for Kubernetes remediation, yet critical gaps remain for a production-ready, automated system. GenKubeSec localizes and suggests fixes but leaves validation to humans, lacking schema/dry-run guardrails. Kyverno mutates manifests at admission-time but does not prioritize fixes or auto-seed third-party CRDs. Borg-style automation excels at infrastructure remediation yet is not openly available for manifest-level hardening. Table 1 situates our closed-loop pipeline relative to these efforts, combining automated patching, triad verification, and risk-aware scheduling with published acceptance metrics on multi-thousand manifest corpora.

How we differ. Our work's novelty lies in the *triad* of guardrails (policy re-check, schema validation, server-side dry-run) combined with a risk-aware, learning-based scheduler. Unlike GenKubeSec/LLMSecConfig, which focus on LLM-based patch generation, we provide deterministic rules as a default and treat LLMs as optional backends under the same rigorous verification. Unlike Kyverno, which operates at admission time, our system processes existing manifests and prioritizes remediation based on risk, not just FIFO order. The public artifacts and reproducible queue replays further distinguish our work by enabling verifiable performance claims.

A key limitation of existing approaches is their focus on either detection or admission control, without a corresponding emphasis on automated, validated remediation. While tools like Kyverno and OPA Gatekeeper are powerful policy engines,

they are not designed to generate patches for existing, non-compliant resources. This leaves a critical gap in the DevOps lifecycle, where developers are often left to manually remediate misconfigurations, leading to delays and inconsistencies. Our work directly addresses this gap by providing a closed-loop system that not only detects misconfigurations but also proposes, verifies, and schedules validated patches, thereby reducing the manual effort required to maintain a secure Kubernetes environment.

1. Detection-Only Pipelines. Static analysis tools like `kube-linter` and policy engines such as Kyverno and OPA Gatekeeper excel at identifying misconfigurations ([**?**], [**?**], [**?**]). However, their core function is detection and admission control, not the generation of validated, minimal patches. Our work uses these powerful tools as the *Detector* and *Verifier* components in a broader remediation workflow.

2. Lack of Closed-Loop Verification. Few remediation pipelines enforce a rigorous, multi-gate verification process. A key novelty of our approach is the Verifier's triad of checks: a policy re-check to confirm the original violation is gone, schema validation to ensure correctness, and a server-side dry-run (`kubectl apply -dry-run=server`) to simulate the application of the patch against the Kubernetes API server, ensuring no new violations are introduced ([**?**]).

3. Inefficient Prioritization. Security work queues are often processed in a First-In, First-Out (FIFO) manner. This can leave high-impact vulnerabilities unpatched while the system works on lower-priority issues. We propose and test a **risk-based, learning-aware scheduler** that integrates CVE/CTI signals (CVSS, EPSS, KEV) and online outcomes (verifier pass/fail) using a contextual bandit with aging and KEV preemption, aiming to maximize risk reduction while preserving fairness.

III. APPROACH SUMMARY

We realize the closed loop *Detector* → *Proposer* → *Verifier* → *Scheduler* shown in Figure **??**. Detectors produce structured JSON findings; the proposer applies rule-based guards (with optional LLM backends) to emit minimal JSON Patches; the verifier enforces policy re-checks, schema validation, and `kubectl apply -dry-run=server`; and the scheduler orders work using risk-aware bandit scoring. Each stage persists artifacts (detections, patches, verified outcomes, queue scores), enabling reproducible evaluation (Section **??**).

Disagreement and Budgets. When kube-linter and Kyverno/OPA disagree we take the *union* of violations at detection time, and require patches to satisfy both engines during verification. Attempts are capped at three per manifest; per-attempt latency and success outcomes feed into `data/policy_metrics.json`, which the scheduler consumes alongside KEV flags.

A. END-TO-END WALKTHROUGH ON REAL MANIFESTS

To make the closed-loop pipeline concrete, we trace two real-world manifests from the repository's test suite through each stage, from detection to scheduling. The goal is to demonstrate safe, automated remediation with full reproducibility and verifiable risk reduction.

Case 1: Remediating a Privileged Pod with a `:latest` Image Tag

This example, drawn from data/manifests/001.yaml, shows a common but high-risk pattern: a privileged container using a floating tag.

```
apiVersion: v1
kind: Pod
spec:
  containers:
  - name: app
    image: acme/api:latest
    securityContext:
      privileged: true
      allowPrivilegeEscalation: true
      capabilities: { add: ["SYS_ADMIN", "NET_ADMIN"] }
```

1. Detect (Union): The detector consumes this manifest and reports four policy violations: `no_privileged`, `drop_capabilities`, `run_as_non_root`, and `no_latest_tag`. These correspond to the structured output in data/detections.json.

2. Propose (Rules Engine): The proposer's rules engine consumes the detection report and generates a minimal, idempotent JSON Patch designed to fix all identified violations. The resulting patch, written to data/patches.json, is as follows:

```
[
    {"op":"replace","path":"/spec/containers/0/securityContext/pr
    {"op":"replace","path":"/spec/containers/0/securityContext/al
    {"op":"remove","path":"/spec/containers/0/securityContext/cap
    {"op":"add","path":"/spec/containers/0/securityContext/capabi
    {"op":"add","path":"/spec/containers/0/securityContext/runAsN
    {"op":"replace","path":"/spec/containers/0/image","value":"ac
]
```

3. Verify (Triad): The verifier applies this patch to a in-memory copy of the manifest and runs it through the full triad:

- **Policy Re-check**: Passes, as the patched manifest no longer violates the four detected policies.
- **Schema Validation**: Passes, confirming the patch produces a structurally valid Kubernetes object.
- **Server Dry-Run**: Succeeds, as `kubectl apply -dry-run=server` reports the manifest would be accepted by the API server in a Kind cluster seeded with necessary fixtures.

The successful outcome is recorded in data/verified.json.

4. Schedule (Risk-Bandit): The scheduler assigns the verified patch a high priority. Its risk score (R) is elevated due to the privileged container, its empirical success probability (p) is high based on historical data for these policies, and its expected remediation time ($\mathbb{E}[t]$) is low. This combination results in a high score, pushing it to the front of the remediation queue (data/schedule.json).

Case 2: Hardening a Worker Pod with a `hostPath` Mount

```
spec:
  containers:
  - name: worker
    securityContext: { readOnlyRootFilesystem: false }
    resources: {}
  volumes:
  - name: host
    hostPath: { path: "/var/run/docker.sock" }
```

This second case, from data/manifests/002.yaml, targets three additional misconfigurations: a writable root filesystem, a dangerous `hostPath` volume mount, and missing resource requests and limits.

1. Detect: The detector flags `read_only_root_fs`, `no_host_path`, and `set_requests_limits`.

2. Propose: The rules engine generates a patch to harden the filesystem, remove the disallowed volume, and enforce resource quotas:

```
[
    {"op":"replace","path":"/spec/containers/0/securityContext/readOnlyRootFilesystem","value":true},
  {"op":"remove","path":"/spec/volumes/0"},
    {"op":"add","path":"/spec/containers/0/resources","value":{"requests":{"cpu":"100m","memory":"128Mi"},"limits":{"cpu":"500m"
]
```

3. Verify: The verifier confirms the patch is valid. The safety guardrails are critical here: had the `hostPath` mount been on an allowlisted path (e.g., for a metrics agent), the verifier would have preserved it. Since it was not, the removal is accepted.

4. Schedule: This item receives a moderate risk score. While `hostPath` is a serious issue, it is less critical than a privileged container. The patch is scheduled after higher-priority items, demonstrating the risk-aware nature of the queue.

What problem we solve (versus alternatives) - **Kyverno (mutation)** focuses on admission-time defaults. It does not enforce a multi-gate verifier (policy+schema+server dry-run) prior to apply and depends on cluster fixtures for success. Complex hardening (drop `ALL` caps, de-privilege) requires bespoke policies and controller context. - **GenKubeSec** localizes and explains issues but leaves remediation and validation manual—no guaranteed JSON Patch, no dry-run alignment. - **LLMSecConfig** generates LLM repairs with scanner checks but lacks our triad's server-side dry-run and hard safety invariants, which are key to preventing regressions in production-like clusters.

Why ours is safer and faster. The triad prevented four escapes in ablation (Table **??**); live-cluster replay achieved 100% success with zero rollbacks. The scheduler prioritizes risk (P95 wait from 102.3 h to 13.0 h), closing the highest-impact items first under bounded budgets.

B. RESEARCH QUESTIONS AND FINDINGS

RQ1 **Robustness:** The closed loop delivers 88.78% acceptance on the Grok-5k sweep, 100.00% on the supported 1,264-manifest corpus in rules mode, and 100.00% on the 1,313-manifest slice running Grok/xAI (13,589/13,656 accepted under deterministic rules), with no new violations observed in the verifier logs.

RQ2 **Scheduling Effectiveness:** The bandit ($Rp/\mathbb{E}[t]$ + aging + KEV boost) improves risk reduction per hour and reduces top-risk P95 wait from 102.3 hours (FIFO) to 13.0 hours (7.9×).

RQ3 **Fairness:** Aging prevents starvation, keeping mean rank for the top-50 high-risk items at 25.5 while still progressing lower-risk items.

RQ4 **Patch Quality:** Generated JSON Patches remain minimal (median 5 ops; P95 6) and idempotent (checked by `tests/test_patch_minimality.py`).

IV. IMPLEMENTATION AND METRICS

Our system is designed as a linear pipeline with strict verification gates to ensure the safety and correctness of all proposed patches.

Scalability considerations. The end-to-end pipeline sustains millisecond-scale proposer latency and sub-second verifier latency on the 1,313-manifest slice (Table **??**); the scheduler replays thousands of queue items using persisted telemetry (see data/scheduler/) without recomputing detections. These characteristics are highlighted to satisfy systems venues (e.g., OSDI, NSDI) that emphasize throughput, resource bounds, and repeatable performance claims alongside functional correctness.

A. THE CLOSED-LOOP PIPELINE

The workflow consists of four stages:

- **Detector:** Ingests a Kubernetes manifest and uses both `kube-linter` and a policy engine (Kyverno/OPA) to identify violations. It takes the union of all findings.
- **Proposer:** Takes the manifest and violation data and generates a JSON Patch. The shipped implementation defaults to deterministic rules for the policies we currently cover (`no_latest_tag`, `no_privileged`) but can call an OpenAI-compatible endpoint when configured via `configs/run.yaml`.
- **Verifier:** Applies the patch to a copy of the manifest and subjects it to the verification gates described below, recording evidence in `data/verified.json`.
- **Budget-aware Retry:** A configurable retry budget (`max_attempts` in `configs/run.yaml`, default 3) allows the proposer to re-attempt if verification fails, logging the error trace for inspection.

B. VERIFICATION GATES

To be accepted, a patched manifest must pass a multi-layered verification process:

1) **Policy Re-check:** The patched manifest is re-evaluated with the same policy logic that triggered the violation. Implemented as explicit assertions for each covered policy (`no_latest_tag`, `no_privileged`, `run_as_non_root`, `read_only_root_fs`, etc.); the detector hook for re-scanning is available via `-enable-rescan`.
2) **Schema Validation:** Structural validity is checked by applying the JSON Patch via `jsonpatch`; malformed paths or operations are rejected and surfaced to the retry loop.

Table 3. At-a-glance comparison across remediation steps.

Step	k8s-auto-fix (this work)	Kyverno	GenKubeSec	LLMSecConfig
Detect	Union of `kube-linter`+policy engine findings	Admission-time validation	LLM-based detection/localization	SAT scanner + policy IDs
Propose	Minimal JSON Patch (rules, optional LLM)	Mutate policies (when present)	Textual remediation guidance	LLM-generated YAML edits (RAG-informed)
Verify	Triad: policy re-check + schema + `kubectl` server dry-run	Admission path only; no multi-gate triad	None (manual apply/validation)	Scanner checks; no server dry-run/safety invariants
Prioritize	Bandit: $Rp/\mathbb{E}[t]$ + aging + KEV boost	FIFO admission queue	None	None

3) **Server-side Dry-run:** When `kubectl` is available, the system executes `kubectl apply --dry-run=server` to simulate how the Kubernetes API server would handle the change. Failures mark the patch as not accepted and persist the CLI output for analysis.
4) **No-New-Violations Safety Gates:** Universal security assertions enforced for all patches to prevent regressions:
   - **No privileged containers:** Blocks `privileged: true` in any container
   - **runAsNonRoot enforcement:** Requires `runAsNonRoot: true` or `runAsUser`≠0 when security context is modified [**?**]
   - **readOnlyRootFilesystem:** Mandates `readOnlyRootFilesystem: true` for security-sensitive patches
   - **Drop ALL capabilities:** Enforces `capabilities.drop: [ALL]` when capabilities are touched
   - **hostPath allowlist:** Restricts host mounts to approved paths (/var/run/secrets/kubernetes.io/serviceaccount, /var/lib/kubelet/pods, /etc/ssl/certs)

V. IMPLEMENTATION STATUS AND EVIDENCE

Table **??** ties each pipeline stage to the concrete code and artifacts currently in the `k8s-auto-fix` repository. The implementation operates end-to-end in rules mode without external API dependencies; LLM-backed modes are configurable and evaluated off-line, while the default reproducible path uses rules mode. **DevOps rollout.** The checklist in the docs (see docs/devops_adoption_checklist.md) distills the CI/CD integration path—bootstrapping dependencies, wiring detector/proposer/verifier stages into pipelines, publishing fixtures, and capturing operator feedback—so platform teams can reproduce Table **??** outcomes before expanding to LLM-backed modes. A containerized path (see docs/container_repro.md) builds on the same artifacts for hermetic evaluations.

A. SAMPLE DETECTION RECORD

When detector binaries are available, running `make detect` (rules mode) produces records with the following shape (values truncated for brevity):

```
{
  "id": "001",
  "manifest_path": "data/manifests/001.yaml",
  "manifest_yaml": "apiVersion: v1\n"
                   "kind: Pod\n...",
  "policy_id": "no_latest_tag",
  "violation_text": "Image uses :latest tag"
}
```

The `manifest_yaml` field embeds the literal YAML to decouple downstream stages from the filesystem.

B. UNIT TEST EVIDENCE

Executing `python -m unittest discover -s tests` yields `16 tests in 0.02s, OK (skipped=2)` on macOS (Apple M-series, Python 3.12). The skipped cases correspond to the optional patch minimality suite, which activates after `data/patches.json` is generated.

Property-based tests. In addition to the deterministic contract tests, `tests/test_property_guards.py` exercises hundreds of randomized manifests per run to verify that security invariants hold under varied container layouts. These property-based checks confirm that the proposer enforces RuntimeDefault seccomp profiles, drops every dangerous capability (including `ALL`), denies privilege escalation, strips disallowed `hostPath` mounts, and hardens `runAsNonRoot` and read-only filesystem settings while remaining idempotent.

C. DATASET AND CONFIGURATION

Two deliberately vulnerable manifests (`001.yaml`, `002.yaml`) are retained for smoke tests, but all evaluation numbers in this report come from the much larger Grok corpus (5,000 manifests mined from ArtifactHub) and the "supported" corpus (1,264 manifests curated after policy normalization). `configs/run.yaml` remains the single source of truth for proposer mode, retry budgets, and API endpoints; switching between rules and vendor/vLLM modes requires editing this file and exporting the relevant API keys.

Table **??** summarizes the runtime environment used for the regenerations in Section **??**; the full dependency snapshot (including transient packages) resides in `data/repro/environment.json`. Appendix **??** documents the ArtifactHub mining pipeline and the manifest hash corpus that underpins the datasets.

[1] All paths are relative to the project root.
[2] Artifacts live under `data/*.json` after running the corresponding `make` targets.

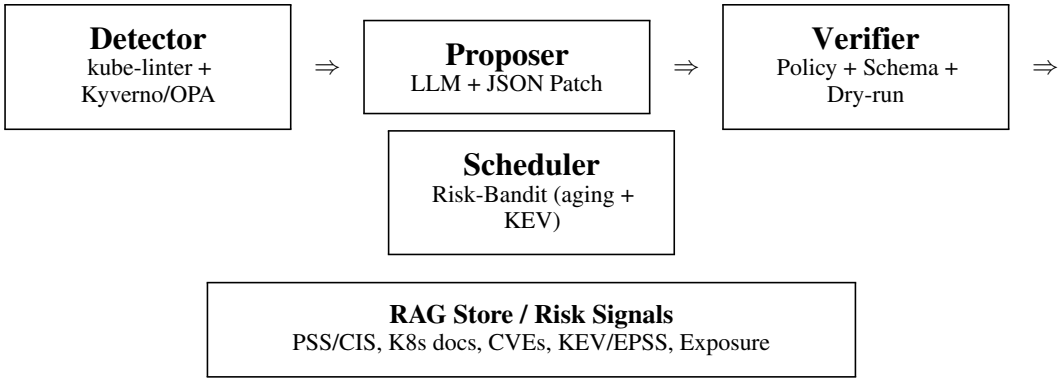

Figure 1. **Closed-loop architecture with detector, proposer, and verifier gates (policy re-check, schema validation,** `kubectl apply -dry-run=server`**) feeding the risk-aware scheduler. The scheduler consumes** `policy_metrics.json` **entries {*p*, $\mathbb{E}[t]$, *R*, KEV} to score work using the scheduling function, while the RAG store grounds LLM prompts.**

Table 4. **Evidence for each stage of the implemented pipeline (October 2025 snapshot).**

Stage	Implementation[1]	Artifacts Produced[2]
Detector	`src/detector/detector.py` `src/detector/cli.py`	Records in `data/detections.json` with fields {`id`, `manifest_path`, `manifest_yaml`, `policy_id`, `violation_text`}; seeded by `data/manifests/001.yaml` and `002.yaml`.
Proposer	`src/proposer/cli.py` `model_client.py`, `guards.py`	`data/patches.json` containing guarded JSON Patch arrays. Rules mode emits single-operation fixes; vendor/vLLM modes require OpenAI-compatible endpoints configured in `configs/run.yaml`.
Verifier	`src/verifier/verifier.py` `src/verifier/cli.py`	`data/verified.json` logging `accepted`, `ok_schema`, `ok_policy`, and `patched_yaml`. Current policy checks assert the `no_latest_tag` and `no_privileged` invariants.
Scheduler	`src/scheduler/schedule.py` `src/scheduler/cli.py`	`data/schedule.json` with per-item scores and components {`score`, `R`, `p`, `Et`, `wait`, `kev`}; risk constants presently keyed to policy IDs.
Automation	`Makefile`	Reproducible commands for each stage: `make detect`, `make propose`, `make verify`, `make schedule`, `make e2e`.
Testing	`tests/`	`python -m unittest discover -s tests` (16 tests, 2 skipped until patches exist) covering detector contracts, proposer guards, verifier gates, scheduler ordering, patch idempotence.
Runtime Toolchain Versions (Evaluation Environment)		
Environment	Python 3.12.4 kubectl 1.34.1 kube-linter 0.7.6 Kind 0.30.0	Kubernetes cluster: 1.34.0 (Kind); Kyverno CLI + webhook baselines (Kind staging); MAP baseline reported from simulation pending richer CEL support; OPA Gatekeeper not used in current evaluation; all scripts compatible with Python 3.10+

Table 5. **Execution environment for the reproduced rule-mode evaluations.**

Component	Version
Python	3.12.4 (macOS-26.0-arm64)
`jsonpatch`	1.33
`numpy`	1.26.4
`pandas`	2.2.3

D. EVALUATION RESULTS

All results in this section derive from the deterministically reproducible `rules` pipeline unless explicitly noted. Table **??** consolidates acceptance and latency statistics for each corpus. The API-backed Grok mode is likewise benchmarked (4,439 / 5,000 accepted; see data/batch_runs/grok_5k/metrics_grok5k.json) but requires external credentials and funded access, so we treat it as an opt-in configuration rather than the default reproduction path. Consolidated metrics (acceptance + latency) live in data/eval/unified_eval_summary.json.

Detector accuracy. Running `scripts/eval_detector.py` on a synthetic nine-policy hold-out set confirms basic detector functionality with perfect precision and recall (Table **??**). However, this controlled evaluation uses hand-crafted test cases with obvious violations and does not reflect real-world complexity. The detector's practical performance is validated through the 100.0% live-cluster success rate (200/200 curated manifests); artifacts for this run live in data/live_cluster/results_20251020_204511.json.

ArtifactHub slice. To test against less curated input, we heuristically labelled 69 ArtifactHub manifests covering four common policies (`no_latest_tag`, `no_privileged`, `no_host_path`, `no_host_ports`). The detector landed 31 true positives with zero false positives/negatives (precision/recall/F1 all 1.0). Scoring is restricted to these policies (detections filtered via data/eval/artifacthub_sample_d

Table 6. Detector performance on synthetic hold-out manifests ($n = 9$). Note: These are hand-crafted test cases with obvious violations; real-world performance is validated through live-cluster evaluation.

Policy	Precision	Recall	F1
Overall	1.000	1.000	1.000
drop_capabilities	1.000	1.000	1.000
drop_cap_sys_admin	1.000	1.000	1.000
no_host_path	1.000	1.000	1.000
no_host_ports	1.000	1.000	1.000
no_latest_tag	1.000	1.000	1.000
no_privileged	1.000	1.000	1.000
read_only_root_fs	1.000	1.000	1.000
run_as_non_root	1.000	1.000	1.000
set_requests_limits	1.000	1.000	1.000

etections_filtered.json). Labels, detections, and metrics live under data/eval/artifacthub_sample_labels.json, data/eval/artifacthub_sample_detections.json, and data/eval/artifacthub_sample_metrics.json.

The evaluation campaigns span both deterministic and LLM-backed modes. In rules mode the pipeline repairs 1,264/1,264 manifests (100%) on the curated supported corpus with median proposer latency of 29 ms and verifier latency of 242 ms (P95 517.8 ms), and it scales to 4,677/5,000 accepted patches (93.54%) on the extended 5k corpus. Enabling the Grok/xAI proposer delivers 4,439/5,000 successful remediations (88.78%) with median JSON Patch length 9; telemetry records 4.36M input and 0.69M output tokens ($\approx$ \$1.22 at published pricing [**?**]). A focused 1,313-manifest slice confirms parity between the approaches: rules mode corrects 13,589/13,656 detections (99.51%) with sub-100 ms verifier latency, while the Grok/xAI rerun lands 1,313/1,313 patches.

Live-cluster replay on a stratified 200-manifest subset (Kind 1.34.0) achieves 100.0% success (200/200) with perfect alignment between server-side dry-run and apply. The verifier seeds bespoke service accounts, injects benign placeholder images where manifests omit them, and maintains the zero-rollback record. Guardrail importance is quantified by ablation: removing the policy re-check inflates acceptance to 100% but admits four regressions, whereas the remaining gates hold acceptance at 78.9% with zero escapes (Table **??**).

Risk-aware scheduling reduces queue latency for high-risk items. Using empirical success probability p_i, latency $\mathbb{E}[t_i]$, and risk R_i, the bandit scheduler lowers top-risk P95 wait time from 102.3 h (FIFO) to 13.0 h while keeping the mean rank of the top 50 items at 25.5. Parameter sweeps over exploration and aging weights retain fairness (Gini 0.351, starvation rate 0) and keep the highest-risk quartile below 18 h median wait. Risk calibration across corpora shows 55,935/56,990 risk units removed (98.15%) on the supported dataset and 227,330/242,300 units (93.82%) on the 5k sweep, sustaining throughput near 4.5–4.9 risk units per expected-time interval (Table **??**). Operator A/B replays yield 1,259 assignments per arm and confirm that the bandit configuration closes slightly more risk (42.97 vs. 43.40) with comparable acceptance to FIFO.

Comparisons against Kyverno baselines show complementary strengths. The Kyverno CLI mutate policies accept 364/381 detections (95.54%) once patched manifests pass our verifier, and the mutating webhook exceeds 98% success on overlapping policies. Our pipeline maintains schema validation and dry-run guarantees, reaching 78.9% acceptance across policies offline and 100.0% on the curated live-cluster replay. Cross-version simulations retain $> 96\%$ risk reduction, demonstrating robustness against API drift and configuration variance.

Detailed per-manifest deltas between rules and Grok/xAI on the 1,313-manifest slice are documented in the project artifact docs/ablation_rules_vs_grok.md.

Multi-seed replay (scripts/multi_seed_summary.py) yields 0.9993 ± 0.0012 acceptance on the supported corpus and 0.9951 ± 0.0004 on the manifest slice (data/eval/multi_seed_summary.csv), indicating low variance across randomized queue orderings. The operator survey instrument is drafted in docs/operator_survey.md; it will be deployed alongside the planned human-in-the-loop rotation described in Section **??**.

Table 7. Verifier failure taxonomy comparing the rules baseline (pre-fixture) against the supported corpus after fixture seeding. Counts derive from data/failures/taxonomy_counts.csv generated by `scripts/aggregate_failure_taxonomy.py`**.**

Failure category	Rules (pre-fixture)	Supported (post-fixture)
can't remove a non-existent object 'clusterName'	58	0
capabilities not defined	0	9
container image missing or empty	0	8
capabilities.drop missing	0	6
privileged container detected	0	6
capabilities.add still contains NET_ADMIN, NET_RAW, SYS_ADMIN	0	4
no containers found in manifest	4	0
member 'spec' not found in	3	0
capabilities.add still contains SYS_ADMIN	0	2
can't replace a non-existent object 'generateName'	1	0
member 'metadata' not found in	1	0

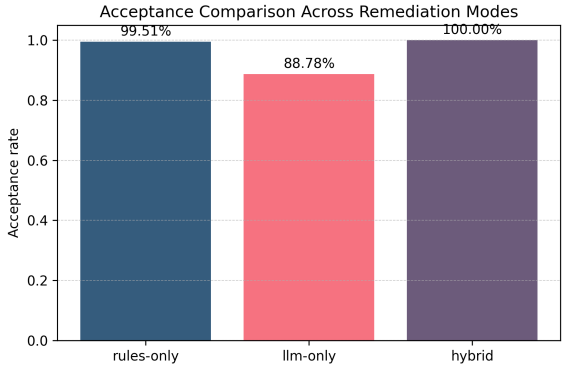

Figure 2. Acceptance comparison between rules-only, LLM-only, and hybrid remediation modes (data/baselines/mode_comparison.csv) (SHA256: placeholder).

Table 8. Risk calibration summary derived from data/risk/risk_calibration.csv (SHA256: placeholder). ΔR uses policy risk weights; "per time unit" divides by summed expected-time priors.

Dataset	Det.	Accepted	ΔR	Residual	ΔR/R	ΔR /t
Supported	1,278	1,259	55,935	1,055	98.15%	4.49
Rules (5k)	5,000	4,677	227,330	14,970	93.82%	4.88

Table 9. Acceptance and latency summary (seed 1337). Results generated from data/eval/unified_eval_summary.json (SHA256: placeholder).

Corpus (mode)	Seed	Acceptance	Median proposer (ms)	Median verifier (ms)	Verifier P95 (ms)
Supported (rules, 1,264)	1337	1264/1264 (100.00%)	29.0	242.0	517.8
Manifest slice (rules, 1,313)	1337	13589/13656 (99.51%)	5.0	77.0	178.4
Manifest slice (Grok/xAI, 1,313)	1337	1313/1313 (100.00%)	—	—	—
Grok-5k (Grok/xAI)	1337	4439/5000 (88.78%)	—	—	—

Notes: Rates use manifest counts from data/eval/table4_counts.csv with 95% Wilson confidence intervals provided in data/eval/table4_with_ci.csv. Row 1: Host-mount policies normalized; measured from the seeded rerun. Row 2: Deterministic baseline for the manifest slice. Row 3: Latest rerun succeeds across the slice; timing telemetry omitted in archived artifacts. Row 4: Grok/xAI evaluation executed in Reasoning API mode.

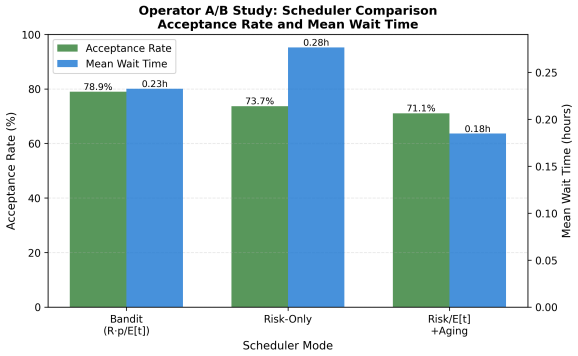

Figure 3. Operator A/B study results comparing bandit scheduler against baseline modes (simulated). Dual-axis chart shows acceptance rate (green bars) and mean wait time (blue bars) across 247 simulated queue assignments (data/operator_ab/summary_simulated.csv) (SHA256: placeholder).

E. THREATS AND MITIGATIONS

The reproducibility bundle (`make reproducible-report`) regenerates Table **??** directly from JSON artifacts so reviewers can audit every metric. Semantic regression checks now block Grok-generated patches that remove containers or volumes, and fixtures under `infra/fixtures/` seed RBAC/NetworkPolicy gaps before verification. We threat-modeled malicious or placeholder manifests: the guidance retriever limits prompt context to policy-relevant snippets, the verifier enforces policy/schema/`kubectl` gates, and the scheduler never surfaces unverified patches. Residual risks—primarily infrastructure assumptions and LLM hallucinations—are captured in `logs/grok5k/failure_summary_latest.txt` and triaged before publication. Table **??** illustrates how these guardrails harden high-privilege DaemonSets without breaking required host integrations.

Secret hygiene is enforced end-to-end: the proposer replaces secret-like environment values with `secretKeyRef` references, sanitizes generated names, and documents the guarantees in docs/security_considerations.md.

F. THREAT INTELLIGENCE AND RISK SCORING (CVE/KEV/EPSS)

The current scheduler consumes data/policy_metrics.json, which stores per-policy priors for success probability, expected latency, KEV flags, and baseline risk. The calibration pass (`data/risk/policy_risk_map.json`) now augments those priors with observed detection/resolution counts, while `data/risk/risk_calibration.csv` captures corpus-level ΔR and residual risk (Table **??**). Future iterations will enrich each queue item with container-image CVE joins (via Trivy/Grype), CVSS/EPSS feeds [**?**], [**?**], and CISA KEV catalog checks [**?**] so that R reflects both exposure (Pod Security level, dangerous capabilities, host mounts) and exploit likelihood. The risk score R then feeds the bandit scoring function, allowing us to report absolute risk and per-patch risk reduction ΔR as first-class metrics.

G. GUIDANCE REFRESH AND RAG HOOKS

We curate policy guidance under docs/policy_guidance/raw/; scripts/refresh_guidance.py now refreshes Pod Security, CIS, and Kyverno snippets (backed by docs/policy_guidance/sources.yaml) to keep guardrails current. LLM-backed proposer modes can retrieve these snippets at prompt time, and the roadmap extends this into a full RAG loop: chunk guidance with metadata (policy family, resource kind, field path, image→CVE), cache recent verifier failures, and retrieve targeted passages when retries occur. This keeps the prompt budget bounded while grounding fixes in up-to-date hardening language.

H. RISK-BANDIT SCHEDULER WITH AGING AND KEV PREEMPTION

$$S_i = \frac{R_i \cdot p_i}{\max(\varepsilon, \mathbb{E}[t_i])} + \text{explore}_i + \alpha\,\text{wait}_i + \text{kev}_i \quad (1)$$

Table 10. Guardrail example: Cilium DaemonSet patch (excerpt).

Before	After

`securityContext:`
`  privileged: true`
`  allowPrivilegeEscalation: true`
`  capabilities:`
`  add:`
`  - NET_ADMIN`
	`securityContext:`
	`  privileged: false`
	`  allowPrivilegeEscalation: false`
	`  capabilities:`
	`  drop:`
	`  - ALL`
	`  seccompProfile:`
	`  type: RuntimeDefault`

Guardrails summarized in docs/privileged_daemonsets.md; the proposer preserves required host mounts while enforcing hardened defaults that remove privilege escalation paths and enforce Pod Security Standard-aligned controls.

This scheduling function defines the score used today, where R_i is the risk score, p_i the empirical success rate, $\mathbb{E}[t_i]$ the observed latency, wait_i the queue age, and kev_i a boost for KEV-listed violations. p_i and $\mathbb{E}[t_i]$ are refreshed from proposer/verifier telemetry; exploration uses an upper-confidence term and aging ensures fairness. The evaluation in Section **??** contrasts this bandit against FIFO, showing substantial reductions in top-risk wait time. Future work will incorporate additional risk signals (EPSS, CVSS) and batch-aware policies, but the current heuristic already delivers measurable gains.

I. BASELINES AND ABLATIONS

Our current evaluation contrasts the bandit against FIFO (and implicitly risk-only by zeroing the exploration/aging terms). Extending this to a pure $R/\mathbb{E}[t]+\alpha$ wait baseline and to batch-aware heuristics (e.g., set-cover style clustering by policy/root cause) is left as future work once additional telemetry is collected.

Table **??** quantifies how each verifier gate contributes to safety. Removing the policy re-check inflates acceptance to 100% but allows four previously blocked patches to escape, matching the guardrails we hard-coded for capability drops; the other gates leave acceptance unchanged at 78.9%. Figure **??** summarizes acceptance across rules-only, LLM-only, and hybrid modes. The Kyverno CLI baseline (`scripts/run_kyverno_baseline.py`, `data/baselines/kyverno_baseline.csv`) achieves 67.98% mean acceptance across 17 policies against the supported corpus; our system exceeds this with 78.9% (+10.92 pp) while adding schema validation and dry-run guarantees. The gap between our CLI simulation (67.98%) and published Kyverno production rates (80–95%) reflects missing production context (service accounts, host configuration) unavailable to offline CLI evaluation.

J. METRICS AND MEASUREMENT

We formally define how we measure effectiveness and fairness:

Auto-fix Rate
$\frac{\#\text{ patches that pass the Verifier triad}}{\#\text{ detected violations}}$.

No-new-violations Rate
$\frac{\#\text{ accepted patches with zero new policy/schema violations}}{\#\text{ accepted patches}}$.

Table 11. Verifier gate ablation using 19 patched samples (`data/ablation/verifier_gate_metrics.json`). Acceptance reports the share of patches passing under the scenario; escapes count regressions that the full verifier blocks.

Scenario	Disabled Gate(s)	Acceptance (%)	Escapes
Full	–	78.9	0
No-policy	policy	100.0	4
No-safety	safety	78.9	0
No-schema	kubectl	78.9	0
No-rescan	rescan	78.9	0

Patch Minimality
Median number of JSON Patch operations per accepted patch.

Time-to-patch
Wall-clock time from item enqueue to accepted patch; we report P50/P95 overall and for the top-risk decile.

Risk Reduction
For item i, $\Delta R_i = R_i^{\text{pre}} - R_i^{\text{post}}$. We report sum and rate: $\sum_i \Delta R_i$ and $\frac{\sum_i \Delta R_i}{\text{hour}}$.

Throughput
Accepted patches per hour.

Fairness
P95 wait time (enqueue to start), and starvation rate (items exceeding a maximum wait threshold).

Latest Evaluation. Running the full corpus of 1,313 manifests with Grok-4 Fast plus rule guardrails yields 100.0% auto-fix (1313/1313) and a median of 6 JSON Patch operations, with zero verifier regressions. Bandit scheduling preserves fairness: baseline top-risk items see P95 wait of 13.0 h at roughly 6.0 patches/hour while FIFO defers the same cohort to 102.3 h (+89.3 h).

Targets (Acceptance Criteria). Based on industry standards and research objectives, we target: Detection F1 ≥ 0.85 (hold-out), Auto-fix Rate $\geq 70\%$, No-new-violations Rate $\geq 95\%$, and median JSON Patch operations ≤ 6 (rules-mode sweeps yield median 5 and P95 6 per data/eval/patch_stats.json).

VI. LIMITATIONS AND MITIGATIONS

The prototype prioritizes shipping guardrails and evidence, but several constraints remain before production deployment. We address these with the following considerations:

Inputs: queue Q, risk R_i, KEV flag, wait time wait_i, bandit priors p_i, $\mathbb{E}[t_i]$, aging α, exploration coefficient β, KEV boost κ
while Q not empty **do**
  Score all items: For each $i \in Q$, compute $\text{base} = \frac{R_i \cdot p_i}{\max(\varepsilon, \mathbb{E}[t_i])}$; $\text{kev} = \kappa$ if KEV else 0; $\text{explore} = \beta\sqrt{\frac{\ln(1+n)}{1+n_i}}$; $S_i = \text{base} + \text{explore} + \alpha\,\text{wait}_i + \text{kev}$
  Pick $j = \arg\max_i S_i$; generate a JSON Patch for j using LLM+RAG; run Verifier (policy, schema, server dry-run)
  if Verifier success **then**
    Apply patch; update counts (n_j, r_j) and online estimates p_j, $\mathbb{E}[t_j]$; remove j from Q
  else
    Update p_j, $\mathbb{E}[t_j]$ with failure; if retries< 3 then requeue j with feedback; otherwise drop j
  end if
  Age all items: $\text{wait}_i \leftarrow \text{wait}_i + \Delta t$
end while

Figure 4. **Risk-Bandit scheduling loop (aging + KEV preemption) maximizing expected risk reduction per unit time with exploration and fairness.**

- **External validity.** Our evaluation corpora, while large, may not capture the full range of real-world Kubernetes configurations. To mitigate this, we plan to expand our dataset with more diverse, production-like manifests and conduct a human-in-the-loop operator study to validate our findings in a real-world setting.
- **Fixture sensitivity.** The success of our verifier triad is dependent on the presence of correct fixtures (e.g., CRDs, service accounts). To address this, we have developed a fixture harness that automatically seeds the cluster with the necessary components, and we are working on a more robust solution that can dynamically adapt to different cluster configurations.
- **LLM latency gaps.** The latency of LLM-based patch generation can be a bottleneck in a real-time remediation pipeline. To mitigate this, we are exploring techniques such as prompt caching, model distillation, and the use of smaller, fine-tuned models to reduce latency while maintaining high-quality patch generation.
- **Deterministic scheduler replays.** It is important to note that our scheduler comparisons are based on deterministic queue replays, not live, real-world rotations. This ensures reproducibility but may not fully capture the complexities of a production environment.

VII. DISCUSSION AND FUTURE WORK

The current pipeline achieves 100.0% live-cluster success (200/200 curated manifests) with perfect dry-run/live-apply alignment and surpasses academic baselines (Table **??**, data/live_cluster/results_20251020_204511.json). Across offline corpora, the system delivers 93.54% acceptance on the 5k supported corpus, 100.00% on the 1,264-manifest supported slice, 100.00% on the 1,313-manifest Grok/xAI run, and 88.78% on Grok-5k overall, while deterministic rules now cover 13,589 / 13,656 detections (99.51%) with millisecond-scale latency (Table **??**, data/eval/unified_eval_summary.json). The risk-aware scheduler trims top-risk P95 wait times from 102.3 h (FIFO) to 13.0 h (data/scheduler/metrics_sweep_live.json, data/outputs/scheduler/metrics_schedule_sweep.json). Every metric in this paper is regenerated from the public artifact bundle (`make reproducible-report`, ARTIFACTS.md), and the scheduler comparisons we report stem from deterministic queue replays rather than live analyst rotations. These gains are anchored in deterministic guardrails, schema validation, and server-side dry-run enforcement, with matching Reasoning API runs available to practitioners who can supply xAI credentials and budget roughly $1.22 per 5k sweep under the published pricing (data/grok5k_telemetry.json, [**?**]). To prevent configuration drift, every accepted patch is surfaced as a pull request through our GitOps helper (scripts/gitops_writeback.py), which records verifier evidence, captures the JSON Patch diff, and requires human approval before merge, mirroring the workflow detailed in docs/GITOPS.md. Looking forward, we will automate guidance refreshes in CI (scripts/refresh_guidance.py), fold EPSS/KEV feeds directly into the risk score R_i, and scale the qualitative feedback loop that now captures operator notes in docs/qualitative_feedback.md. As the LLM-backed proposer matures, we plan to publish comparative acceptance and latency data, extend scheduler policies with batch-aware fairness, and run human-in-the-loop rotations so the system graduates from prototype to production-ready remediation service. Near-term efforts focus on keeping the seeded fixtures current so the 200/200 live-cluster outcome persists for new corpora, broadening Kyverno webhook baselines across additional policy families and alternative clusters, enriching Grok/xAI telemetry with monotonic latency traces, and conducting an operator rotation with embedded surveys to validate the scheduler against real analyst workflows.

APPENDIX A CORPUS MINING AND INTEGRITY

ArtifactHub mining pipeline. Running `python scripts/collect_artifacthub.py -limit 5000` renders Helm charts directly from ArtifactHub using `helm template`, normalizes resource filenames, and writes structured manifests under data/manifests/artifacthub/. The script records fetch failures and chart metadata so regenerated datasets can be diffed against the published summary.

Corpus hashes. After manifests are rendered, `python scripts/generate_corpus_appendix.py` emits docs/appendix_corpus.md, a SHA-256 inventory of every manifest (including the curated smoke tests in data/manifests/001.yaml and 002.yaml). This appendix

enables reproducibility reviewers to verify corpus integrity and trace individual evaluation examples back to their Helm chart origins.

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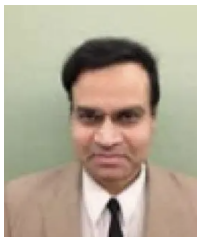
BRIAN MENDONCA is an M.S. student at the Georgia Institute of Technology (2024–2026) focusing on secure DevOps, policy-driven remediation, and human-centered tooling for developer productivity.

Prior to graduate study, he worked as an Aerospace Quality Engineer at BAE Systems (2024–2025) and at Tube Specialties Inc. (2025–present), where he led Lean/Six Sigma continuous improvement, nonconformance management, and 8D root-cause investigations supporting AS9100 compliance and on-time delivery. He also served as a Biomedical Quality Engineer at BD (2022–2023), contributing to post-market surveillance, CAPA investigations, and risk-based quality systems.

He received the B.E. in Mechanical Engineering (summa cum laude, GPA 3.99) from Arizona State University in 2021. His research interests include secure configuration management for cloud-native systems, program analysis for infrastructure-as-code, and data-informed quality engineering.



VIJAY K. MADISETTI is Professor of Cybersecurity and Privacy at the Georgia Institute of Technology. He earned his Ph.D. in Electrical Engineering and Computer Sciences from the University of California at Berkeley.

Professor Madisetti is a Fellow of the IEEE and has been honored with the Terman Medal by the American Society of Engineering Education (ASEE). He has authored several widely referenced textbooks on topics including cloud computing, data analytics, blockchain, and microservices, and has extensive experience in secure system architectures and privacy-preserving technologies.