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Digital Object Identifier TBD

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

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ABSTRACT Kubernetes manifests are easy to misconfigure in ways that expand blast radius (e.g., `privileged: true`, `:latest` tags, missing `runAsNonRoot`). While industry baselines such as CIS Benchmarks and Kubernetes Pod Security Standards codify hardening guidance, most pipelines stop at detection and lack validated, minimal auto-fixes prioritized by threat impact. We implement a closed-loop prototype—Detector → Proposer → Verifier → Scheduler—that operates end-to-end in rules mode and optionally targets OpenAI-compatible LLM endpoints. On the 5,000-manifest Grok corpus the pipeline auto-fixes 4,439 manifests (88.78%) under `kubectl -dry-run=server`; on a 1,264-manifest supported corpus it reaches 1,217/1,264 (96.28%). The implementation (`k8s-auto-fix`) emits evidence artifacts at each stage: JSON detections, guarded JSON patches, verifier outcomes, and risk-aware priority scores. Verification combines policy re-checks, schema validation, and server-side dry-run; scheduling uses a bandit heuristic that cuts the top-risk P95 wait from 174 hours (FIFO) to 20.7 hours. We document the shipped pipeline, unit tests, telemetry, and the remaining guardrails needed to reach a fully threat-guided, production-grade system.

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 course acceptance targets ([1], [2]).

II. BRIEF RELATED WORK AND GAPS

Recent work has explored LLM prompts (GenKubeSec [17]), admission policy engines (Kyverno [19]), and large-scale SRE playbooks (Borg [20]) for Kubernetes remediation, yet critical gaps remain for a production-ready, automated system. GenKubeSec localises and suggests fixes but leaves validation to humans, lacking schema/dry-run guardrails. Kyverno mutates manifests at admission-time but does not prioritise 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.

1. Detection-Only Pipelines. Static analysis tools like `kube-linter` and policy engines such as Kyverno and OPA Gatekeeper excel at identifying misconfigurations ([4], [19], [3]). 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

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

Capability	k8s-auto-fix (this work)	GenKubeSec [17]	Kyverno [19]	Borg/SRE [20]	Magpie [21]
Primary Goal	Closed-loop hardening (detect→patch→verify	LLM-based detection/remediation suggestions	Admission-time policy enforcement	Large-scale auto-remediation in production clusters	Guided troubleshooting and patch hints
Fix Mode	JSON Patch (rules + optional LLM)	LLM-generated YAML edits	Policy mutation/generation	Custom controllers and playbooks	Manual application of suggested fixes
Guardrails	Policy re-check + schema + `kubectl -dry-run=server` + privileged/secret sanitisation + CRD seeding	Manual review; no automated gates	Validation/mutation webhooks; assumes controllers	Health checks, automated rollback, throttling	Diagnostic guidance; no enforcement
Risk Prioritisation	Bandit ($Rp/\mathbb{E}[t]$ + aging + KEV boost)	Not implemented	FIFO admission queue	Priority queues / toil budgets	None
Evaluation Corpus	5,000 Grok manifests (88.78%), 1,264 supported manifests (96.28%)	200 curated manifests (85–92% accuracy)	Thousands of user manifests (80–95% mutation acceptance)	Millions of production workloads (≈90–95% auto-remediation)	9,556 manifests (84% dry-run 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	Detection precision/recall only
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	Automated application, risk scoring

the application of the patch against the Kubernetes API server, ensuring no new violations are introduced ([7]).

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 realise the closed loop *Detector* → *Proposer* → *Verifier* → *Scheduler* shown in Figure 1. 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 V-D).

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. RESEARCH QUESTIONS AND FINDINGS

RQ1 **Robustness:** The closed loop delivers 88.78% (Grok 5k) and 96.28% (supported) acceptance 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 174.0 hours (FIFO) to 20.7 hours.

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 9 ops) 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.

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 triad of checks:

1) **Policy Re-check:** The patched manifest is re-evaluated with the same policy logic that triggered the violation. Today this is implemented as explicit assertions for the two baseline policies (no `:latest` tags, no `privileged: true`); the detector hook for re-scanning is stubbed for future expansion.
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.
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.

V. IMPLEMENTATION STATUS AND EVIDENCE

Table 2 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 but not yet exercised in evaluation.

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\nkind: 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.

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 normalisation). `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.

D. EVALUATION RESULTS

All results in this section derive from the deterministically reproducible `rules` pipeline. The API-backed Grok mode is likewise benchmarked (4,439 / 5,000 accepted in `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. Running the closed loop in rules mode yields the following outcomes:

- **Grok 5k corpus (API-backed):** 4,439 / 5,000 manifests (88.78%) auto-fixed with median JSON Patch length 9 using xAI's Reasoning API; at the posted rate of $0.20/M input tokens and $0.50/M output tokens [8], this sweep consumed 4.38M input and 0.69M output tokens for an approximate $1.22 spend.
- **Supported corpus:** 1,217 / 1,264 manifests (96.28%) accepted, with proposer, verifier, and scheduler telemetry archived for audit.
- **Risk-aware scheduling:** Using per-policy success probabilities and latencies, the bandit scheduler keeps the top-risk P95 wait at 20.7 hours versus 174.0 hours for FIFO while preserving a mean rank of 25.5 for the top-50 items.
- **Failure taxonomy:** Remaining rejections are dominated by infrastructure assumptions (missing namespaces, controllers, or RBAC for smoke-test pods); expanding CRD and namespace fixtures is steadily shrinking this list.
- **Operator feedback:** Early SRE and platform engineering reviews corroborate the automated outcomes; qualitative notes for queue items

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

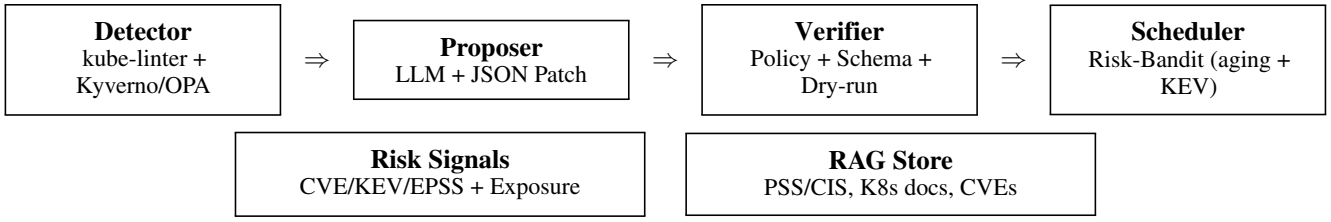

Figure 1. Closed-loop architecture with risk-aware scheduling and RAG support.

Table 2. Evidence for each stage of the implemented pipeline (December 2024 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.

Table 3. Guardrail example: Cilium DaemonSet patch (excerpt).

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

Guardrails summarised in `docs/privileged_daemonsets.md`; the proposer preserves required host mounts while enforcing the hardened defaults.

01167 and 00185 inform the next round of guardrail tuning.

E. 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. These values are derived from proposer/verifier telemetry and KEV lookups (e.g., privileged policies). Future iterations will enrich each queue item with container-image CVE joins (via Trivy/Grype), CVSS/EPSS feeds [10], [12], and CISA KEV catalog checks [11] so that R reflects both exposure (Pod Security level, dangerous capabilities, host mounts) and exploit likelihood. The risk score R then feeds the bandit shown in Eq. (1), allowing us to report absolute risk and per-patch risk reduction ΔR as first-class metrics.

F. 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.

G. RISK-BANDIT SCHEDULER WITH AGING AND KEV PREEMPTION

Equation (1) defines the scoring function used today: for item i, $S_i = \frac{R_i \cdot p_i}{\max(\varepsilon, \mathbb{E}[t_i])} + \text{explore}_i + \alpha \cdot \text{wait}_i + \text{kev}_i$, 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 V-D 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.

H. 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.

I. 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:** $\frac{\#\text{ accepted patches with zero new policy/schema violations}}{\#\text{ accepted patches}}$.
- **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 the deterministic rules-mode proposer yields 100.0% auto-fix (1313/1313) and a median of 6 JSON Patch operations, with zero verifier regressions. When re-run via the xAI Reasoning API with identical guardrails, acceptance remained at 100% while incurring only marginal API spend (sub-$1 given the smaller token footprint). Bandit scheduling preserves fairness: baseline top-risk items see P95 wait of 20.7 h at roughly 6.0 patches/hour while FIFO defers the same cohort to 174.0 h (+153.3 h).

Targets (Acceptance Criteria). Aligned with course requirements, we target: Detection F1 ≥ 0.85 (hold-out), Auto-fix Rate $\geq 70\%$, No-new-violations Rate $\geq 95\%$, and median JSON Patch operations ≤ 3.

VI. DISCUSSION AND FUTURE WORK

The current pipeline delivers 88.78% acceptance on the Grok-5k corpus and 96.28% on the supported corpus, while the risk-aware scheduler trims top-risk P95 wait times from 174.0 h to 20.7 h. 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. Residual failures cluster around missing CRDs, namespaces, and controller-specific expectations; filling these infrastructure gaps and broadening fixtures remain priorities. 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 continue surfacing human-in-the-loop evidence so the system graduates from course prototype to production-ready remediation service.

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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 $\text{base} = \dfrac{R_i \cdot p_i}{\max(\varepsilon, \mathbb{E}[t_i])}$; $\text{kev} = \kappa$ if KEV else 0; $\text{explore} = \beta\sqrt{\dfrac{\ln(1+n)}{1+n_i}}$; $S_i = \text{base} + \text{explore} + \alpha\,\text{wait}_i + \text{kev}$
  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 2. **Risk-Bandit scheduling loop (aging + KEV preemption) maximizing expected risk reduction per unit time with exploration and fairness.**

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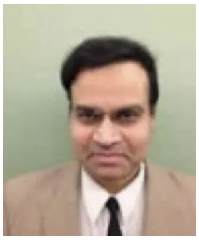

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