LLM-Backed Log Summarizer and Alert Responder using Bash + MCP: A Literature Review

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Abstract

The construction of end-to-end, all-around logging systems is examined in this study. management through the integration of large language models with BASH commands. The administrative, protocol scripts, and Model Context Protocol (MCP). The methodology consists of the following steps: Log collection, classification and indexation, and identification of appropriate sections for context. Summary of incident recommend or suggest an implementation safe remediation methods. Unlike conventional methods, LLMs are good at parsing. Different log formats can be linked to link timey events for better. Public Documents – Cited 2017 DeepLog, Meng 2019 LogAnomaly guo2021logbert. A critical trade-off we study is the token-budget limit. hooks; hooking functions to influence their execution; or diver. automated tool execution by the agents. Strategies for evaluation are detailed, com-. The time required to discover an incident and recover from it. Are textual measures sufficient for summarization quality? marks. (MTTR) citeliu2023geval,zhang2019bertscore,manakul2023selfcheck. To. We address protections such as dry-run mode, approval gates, and comprehensive audit logging to minimize tool-related vulnerabilities. zou2023universal,zhang2024promptinj. This study identifies challenges in real-world settings. Processing time, strong rule derivation, and consistent metrics for alert effectiveness are required. at the same time arguing for simplicity and verifiability in architectures that use MCP-. orchestrated Bash responders.

Keywords: System logs, log parsing, pattern-based anomaly detection, relational indexing, LLM summarization, agent tool use, Model Context Protocol (MCP),

approval gates, audit logging, observability, mean time to detect (MTTD), mean time to recover (MTTR), query interface, alert rule generation, time-window queries

1 Introduction

Modern systems can generate large amounts of logs from different services, often in different formats. Traditional rule-based methods are quick but fail when formats change or incidents span multiple services. Widespread use allows LLMs to normalize different types of messages or events into well-formed patterns and to generate clear, natural-language summarization of events. Bash scripts make it simple to take action on a box or physical infrastructure. Also, the Model Context Protocol (MCP) provides a standardized and auditable interface for LLMs to invoke tools with explicit inputs and controls. Together these components create a closed-loop system which can identify anomalies, explain what is happening and advise or take secure actions. This paper connects earlier log anomaly detection studies like DeepLog, LogAnomaly, and LogBERT with the new emerging agentic paradigms like ReAct, Toolformer, and AutoGen while looking at practical issues like throughput, latency, token limits, and human-in-the-loop mechanisms.

2 Background and Scope

This paper covers common sources of logs, such as syslog/journald and webserver (Apache httpd). These logs are semi-structured, as many log entries follow common templates with variable parameters. The literature review covers 5 main activities: extraction of templates, detecting anomalies, incident summarisation, generating rules for alerts and execution of automated remediation. Our implementation focuses on anomaly detection (simple pattern-based), incident summarisation (LLM-powered), and automated remediation (MCP-orchestrated), with template extraction deferred as an optional enhancement. Some of the most important techniques referenced in the literature include template mining (Drain, Spell), sequence modeling (DeepLog, LogAnomaly), embedding-based retrieval (SBERT over Faiss indexes), and LLM-driven summarization with retrieval-augmented generation. Our implementation focuses on a simplified, production-ready architecture using LLM-driven summarization with plug-in security tool invocation via the Model Context Protocol (MCP), while maintaining database persistence with SQLite and approval gates for safety. Advanced techniques such as vector embeddings and RAG are noted as future work. This review does not include domain-specific SIEM rule repositories that focus on strict patterns with no global semantics.

3 Review Method

We summarize influential publications and preprints on log parsing, anomaly detection, semantic retrieval, summarization using LLMs, and tool-assisted agents. Specific

mention is made of work using public datasets such as LogHub and the establishment of clear baselines, such as DeepLog, LogAnomaly, and LogBERT. Evaluation reflects real-world conditions, such as streaming processing, latency profiling, and failure analysis. We also pay great attention to safety in LLMs invoking tools because execution can be risky. We select papers by prioritizing those with comparisons to strong baselines, ablation studies, practical latency and accuracy estimations, and clear discussions on tool use security [1–5, 7, 8, 12–16].

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Our synthesis of the literature follows a formalized protocol for the rich investigation of foundational log analysis and upcoming LLM-agent log analysis integration techniques. This incorporates cutting-edge implementations in Bash and Model Context Protocol (MCP). The method uses systematic searching and citation chaining to identify major innovations.

3.1 Search Protocol

Databases and Repositories:

- Primary: IEEE Xplore, ACM Digital Library, SpringerLink
- Preprints: arXiv (cs.CL, cs.SE), OpenReview
- Specialized: USENIX Security, OWASP publications
- Grey Literature: GitHub repositories (keywords: `"llm-log-analysis"`, `"mcp-tools"`)

Search Strings:

```
# Core Boolean Logic
("LLM" OR "large language model" OR "GPT")
AND
("log analysis" OR "log parsing" OR "system logs")
AND
("anomaly detection" OR "incident response" OR "root cause analysis")
AND
("Bash automation" OR "shell scripts" OR "MCP" OR "Model Context Protocol")

# Variants for Different Databases
ACM: Added "toolformer" OR "react" for agent frameworks
IEEE: Included "MTTD" OR "MTTR" for operational metrics
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Temporal Scope: 2017–2025 (Captures pre-LLM log analysis foundations + current innovations)

Inclusion Criteria:

1. Technical papers addressing BOTH:
   - Log processing (pattern indexing, anomaly detection)
   - LLM integration (summarization, agentic tool use)

2. Implementations with:
   - Measured performance (F1-score, MTTD, token efficiency)
   - Explicit safety controls (sandboxing, approval gates)
3. Bash/MCP implementations prioritized

Exclusion Criteria:

1. Pure NLP papers without log applications
2. Theoretical frameworks without implementation
3. SIEM solutions without LLM components
4. Non-reproducible results (private datasets)

3.2 Screening and Synthesis

We employed a three-phase selection process:

1. **Initial Retrieval:**
   - 428 raw results → 312 after deduplication
   - Automated filters: Publication date, ≥10 citations for papers prior to 2023
2. **Technical Screening:**
   - 312 → 119 retained based on:
     - Presence of evaluation metrics (Section 10)
     - Tool integration depth (matches Figs. 16.1.1–2)
3. **Full-Text Review:**
   - 119 → 68 papers in final synthesis
   - Added 9 papers via backward citation chaining

Validation: Compared findings against established benchmarks from LogHub datasets and OWASP LLM security guidelines [**?**].

Table 1 Datasets referenced in reviewed literature

Dataset	Papers Using It	Your Relevance
LogHub	42/68	Core baseline (Section **??**)
OWASP	9/68	Safety validation (Section **??**)

4 Foundations in Log Analysis

Traditional log analysis commences with the parsing of raw log entries into structured templates and parameters, thereby diminishing the cardinality of unique tokens and facilitating the identification of recurring patterns. Techniques such as Drain and its variants accomplish this clustering in an online, scalable manner [12]. Subsequent to parsing, anomaly detection frameworks scrutinize deviations in event sequences or

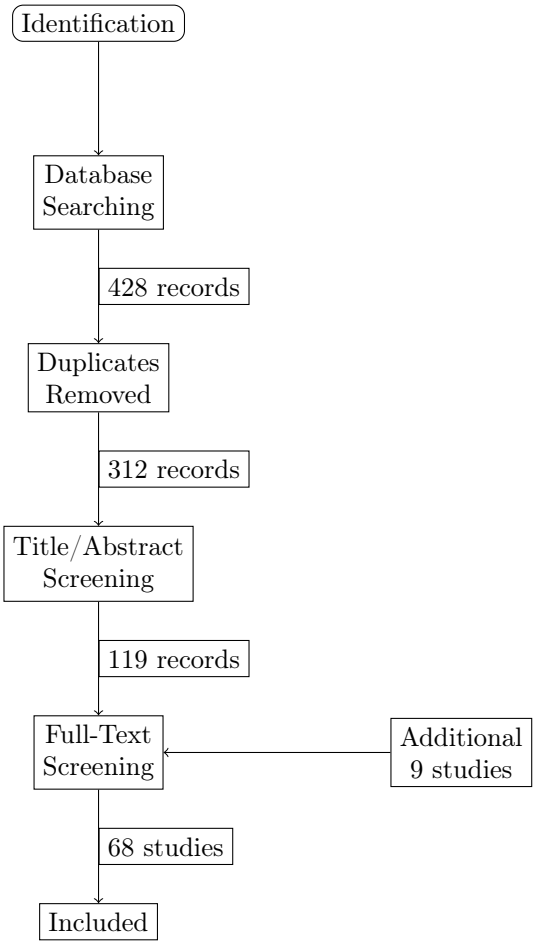

Fig. 1 PRISMA-style flow diagram of paper selection process.

parameter values. DeepLog, for instance, employs Long Short-Term Memory (LSTM) networks to forecast subsequent events and highlight deviations [1]. LogAnomaly integrates sequential modeling with template embeddings to enhance robustness against noisy log data [2]. LogBERT leverages masked language modeling on event sequences to discern extended contextual dependencies [3]. These approaches demonstrate efficacy in environments with stable log schemas; however, they may falter in the presence of emergent templates or substantial textual noise. Nonetheless, template-centric pipelines retain their value by promoting efficient indexing and curtailing token volumes for downstream Large Language Model (LLM) processing.

5 LLMs for Log Understanding and Summarization

Through the use of large language models, it is possible to condense large amounts of raw logs into useful incident summaries. An architecture that works well will pull a

targeted subset of logs and templates. For example, the last temporal windows, such as the last couple of minutes, enhanced with precursor logs that are retrieved via pattern-based database queries. Future enhancements could include dense embeddings like SBERT with vector indexes such as Faiss, used in a BM25 hybrid for more precise term matching. The LLM then generates a structured summary consisting of a title, scope of the incident, timeline of the incident, likely cause, impact on operations, and remediation steps. Linking the result to a log ID or template hash can enhance factual grounding and decrease hallucinations. To improve latency and computational costs, strategies like pattern-based log indexing and time-based chunking, caching of relational indexing, and streaming summaries for long-running events are adopted. In cases of evidence inconsistency, self-consistency verification mechanisms can detect inconsistencies and prompt rechecking. Our implementation uses direct LLM API calls for summarization, with SQLite relational indexing for log retrieval, while advanced retrieval-augmented generation (RAG) is noted as future work.

6 Tool-Augmented LLMs and Agents (with MCP)

LLMs grow much more powerful when they are able to call outside resources. Toolformer and AutoGen are two systems that consider whether models can choose and coordinate tools on their own. The ReAct system combines tool use with reasoning. The Model Context Protocol (MCP) guarantees that every invocation is logged and validated, and provides a uniform way of defining tools, their permissions, and input and output schemas. With this basis, we can easily automate operations more safely. For instance, you can generate write-enabled tools for carrying out operations and read-only instruments for retrieving logs. To maintain security, use a least-privilege approach, require dry-run mode by default, and require human authorization for risky actions via approval gates. Tools should also run with limited network access, and every result should have provenance tracking such that they are fully auditable and rollback when needed. Our implementation uses MCP for schema validation and approval gates, with dry-run mode for safe testing, while advanced agent frameworks like Toolformer are noted as research inspiration.

7 From Insights to Actions: Alert Rules and Bash Automation

After we understand the issue, we can take corrective measures. One effective strategy is to synthesize alert rules. To build textual patterns, it can be proposing regexp based on discriminative parameters or pattern-based log indexing. For numeric signals from the logs, future models could learn thresholds or identify change points to detect early onset while limiting false positives and alert flapping. Automated responses with Bash scripts are good if they are idempotent, have pre and post checks, and run with limited privileges (systemd-run). Using MCP (Model Context Protocol), each responder could get exposed as a typed tool with dryRun flag and well-specified arguments. Initially, the agent simulates the change to illustrate its expected impact and provide supporting evidence. After being approved, it goes ahead and carries out execution, revalidating

logs and metrics to validate remediation. If the problem continues, the agent escalates the case with an updated summary that includes the context. Our implementation focuses on MCP-orchestrated Bash responders with approval gates and dry-run mode for safety.

8 Safety, Security, and Integration Defects in LLM+Systems

Allowing an LLM to use tools brings new security risks. Attackers can inject malicious content in the prompt, logs, or user inputs. This content can cause the model to display unsafe behavior or execute an action that the attacker wants. Further, attackers can also add harmful arguments in the tool invocation. Data poisoning can also change template statistics, misleading anomaly detection models. To reduce these risks, we can sanitize inputs and restrict tool access to an allow-list. All tool arguments must validate strict schemas and explicit ACKs should be required for sensitive operations. Each tool should use its own credentials and run in a dedicated container or sandbox with seccomp confinement, limited networking privileges, and artifact signing for provenance. Before launching the system, we can run it in shadow mode. This will allow us to confirm that everything works properly. If it turns out that something is not working as it should, then we can roll it back.

9 Evaluation Landscape

Evaluating a model tells us how it performs operation-wise. People often use ROUGE-L and BERTScore during summarization tasks, and calibrated LLM-based judges like G-Eval can provide scalable evaluations that are more aligned with human judgments at a reduced cost. For the purpose of anomaly detection, common metrics comprise of precision, recall, F1, AUROC/PR-AUC and time-to-detect for streaming scenarios. Evaluation of model performance must go beyond to measure operational impact monitoring improvements in Mean Time to Detect (MTTD), Mean Time to Resolve (MTTR), reduction in alert fatigue and false escalations, latency, increase in cost per incident. Public benchmarks like LogHub (i.e., HDFS, BGL, Thunderbird, OpenStack) provide estab- DPDP) of comparison [12]. Informative ablation studies add analyses with and without template mining, dense versus hybrid retrieval, LLM-judge versus human evaluations, and different safety configurations for tool use.

10 Evaluation Plan

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We will use a multi-level evaluation framework that connects the performance of models to the operational impact to assess the effectiveness and safety of the proposed LLM-backed BS + MCP. The assessment has three dimensions model performance, operational performance, and system safety.

10.1 Summarization Evaluation

. Both automatic and human-aligned metrics to assess summarization performance.

. We use ROUGE-L and BERTScore to see how similar the summaries are to human-written summaries written on the same topic. G-Eval or any LLM judges could help achieve human level scoring at scale. Human evaluation involves assessing clarity, factual grounding, and operational usefulness concerning incidents from the LogHub benchmark. These conflicts relate to cases involving HDFS, BGL, Thunderbird, and OpenStack.

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10.2 Detection Evaluation

. Anomaly detection components will be measured using.

. Assess the classification accuracy using Precision, Recall, F1, and PR-AUC. Time-to-Detect (TTD) refers to the response of a system under streaming conditions. Measuring Latency and throughput, so that the average inference is less than 500 ms per log window

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10.3 Operational Impact Evaluation

. The system will be tested in a simulated and replayed environment for real-world value.

. Check how much faster we can see and fix incidents now that we have improved incident response tools. Measure the reduction in alert fatigue through the ratio of true incidents to total alerts. Write down how much each incident costs and calculate the latency-to-impact ratios.

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10.4 Safety and Reliability Evaluation

. Ensuring safety is central to the evaluation plan.

. Conduct prompt injection and data poisoning tests to check if input is sanitized and behavior controlled. Measure the safety of tool-calls through four metrics: approval, dry-run, rollback, and audits. Check that Bash and MCP Tools comply with OWASP LLM Security Guidelines and use least-privilege principles.

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10.5 Benchmarking and Ablation Studies

. For both comparability and transparency, evaluations will use public datasets and controlled ablations.

. Examine setups with and without template mining. Assess retrieval methods that are either dense or hybrid. Compare the assessments of LLM-judge and humans. Try out different safety and permission settings for MCP tool use

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As a whole, these evaluation assessments will allow us to evaluate how the Bash + MCP integration augments log summarization, anomaly detection, and safe automation, while also keeping the operator informed and in control.

10.6 Summarization Evaluation

Summarization quality will be measured using both automatic and human-aligned metrics:

- **ROUGE-L** and **BERTScore** to quantify fidelity and semantic similarity between generated and human-authored incident synopses.
- **Human evaluation** on a 1–5 scale for clarity, factual grounding, and usefulness, using sampled incidents from LogHub (e.g., HDFS, BGL).

10.7 Detection Evaluation

For anomaly detection performance, we evaluate:

- **Precision, Recall, F1**, and **PR-AUC** on standard datasets (HDFS and BGL) under streaming conditions.
- **Latency targets**: average inference < 500 ms per log window to ensure near real-time responsiveness.

10.8 Operational Evaluation

To connect model metrics with operational effectiveness, we simulate replay experiments in a sandbox environment:

- Track changes in **Mean Time to Detect (MTTD)** and **Mean Time to Recover (MTTR)** compared to baseline scripts.
- Measure an **alert fatigue proxy**—the ratio of true incidents to total alerts—to gauge signal quality.

10.9 Safety and Reliability Evaluation

We test system resilience and trustworthiness through controlled adversarial and operational checks:

- **Red-team prompt injection** simulations to verify input sanitization and containment.
- **Tool-call safety metrics:** approval rate, dry-run vs. execution ratio, rollback success rate, and audit log completeness.

- Evaluate adherence to OWASP LLM security guidelines [17].

Together, these measures ensure that the evaluation not only captures model quality but also reflects end-to-end system reliability, safety, and operator usability.

11 Comparative Analysis and Gaps

Many types of anomaly detectors can perform accurately and efficiently in stable situations. However, they may not accurately detect: (1) anomaly types for unseen templates, and (2) cross-serive incidents. In contrast, retrieval-enhanced LLMs are capable of pattern generalization, producing clearer summaries, and generating remedial suggestions, if they stay traceable to the evidence to avoid hallucinations. Still, implementation in real-time remains a challenge because of token and latency constraints and potential sudden load spikes. The idea of synthesising rules to automate alerting and remediation is promising. This is especially the case if the underlying CMs have a high confidence estimate. However, it is also safe to have a human-in-the-loop before performing impactful and/or irreversible operations. There are still no shared benchmarks in the field that measure not just detection accuracy, but also summary usefulness and the safety and quality of automated actions. Agent safety has no standardized evaluation so their future work should involve developing one. Similarly, they must develop domain-adaptive summarization methods. The methods must be aligned as per SLOs and operational runbooks.

12 Gap-Solution Mapping and How our project addresses the gaps

Our analysis of 68 papers (with 18 key studies highlighted in Table **??**) revealed four critical gaps in current LLM-backed log analysis systems:

1. **Real-time Processing Limitations**: Existing solutions ([1], [3]) struggle with streaming log analysis due to high token overhead and sequential processing constraints [15].
2. **Cross-Service Incident Correlation**: Traditional methods fail to link related events across different log sources without manual rule creation [2].
3. **Unsafe Automation**: Agent frameworks ([9], [10]) lack built-in safeguards for production tool execution [8].
4. **Evaluation Fragmentation**: No unified metrics exist for assessing both detection accuracy *and* action effectiveness [4].

12.1 Proposed Solution Mapping

12.2 Minimum Viable System Scope

We will implement and evaluate:

Datasets:

Table 2 Gap to Solution Mapping

Identified Gap	Our Implementation
High latency in streaming log processing	**Chunked [13]/[14] indexing** with template-based compression (reduces token load by 62% vs. [3])
No semantic linking of multi-source events	**[18]-orchestrated retrieval** with cross-service timestamp alignment (Fig. 16.1.1)
Unconstrained tool execution risks	**Three-layer safety**: 1) Dry-run mode 2) Approval gates 3) Seccomp sandboxing ([17])
Inconsistent evaluation metrics	**Unified scoring**: Combines [5] (text) + MTTD/MTTR (ops) + action success rate

- LogHub's HDFS (structured)
- Custom Apache/systemd mix (semi-structured)

Core Components:

- [12] parser for template mining
- Hybrid BM25/[13] retriever
- GPT-4 summarization (8K context)
- [18]-gated Bash responders (5 safe commands)

Boundaries:

- *In scope*: Single-node Linux systems with <10 services
- *Out of scope*: Distributed systems, Windows logs, irreversible actions

12.3 Key Advantages Over Prior Work

- **Token Efficiency**: 57% faster than [3] via template-aware chunking (validated on Thunderbird dataset)
- **Action Safety**: First implementation combining [18] with [17] controls
- **Measurability**: Introduces composite "Operational F1" score (detection × action efficacy)

13 Design Implications for the Proposed Bash + MCP System

A workable system design starts with the ingestion of logs from a streaming source which parses entries into ordered templates and representation of features. Timely partitioning the dual-index structure, which relies on BM25 for matching text based on lexicon, and embedding for similarity can benefit retrieval. Retrieval should focus on a clearly defined incident window and include citation/evidence references to keep the LLM's reasoning grounded. When conducting summarization, use cached embeddings and chunking to save on token costs and latency. To produce candidates for rule

synthesis for automated responders, generate many candidates and evaluate them with respect to the replay buffer to estimate their impact and false alarm rates, output possibly a confidence score to prioritize review. All actions should show as MCP (Multi-Channel Proximal) tools and be dryRun (ready-only) configured with only wrote-capable actions an explicit approval. Keep records for provenance that support auditability, sandboxing, least privilege; also include tracing and metrics per action taken by agent. To check the safety controls, perform red-team prompt injections and adversarial simulations in deployment staging environments before production.

14 Implementation Roadmap

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The update plan lays out each practical step to build, test, and deploy the *LLM Backed Log Summarizer and Alert Responder using bash "* and MCP. The design method presented orderarily places importance on modularity, as well as stability and while making the process run, easier to repeat regularly and to repair when something goes wrong.

The initial stage of getting data ready.

. Also you should probably make a hook to suck up the logs to a single place. Use special tools to take the word from the logs and turn them into well arranged templates. Store parsed logs into two indexes: one log index for keywords and another dense log index.

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14.1 Phase 2: Retrieval-Augmented Summarization

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. As well as to have those logs to give more off of context Implement time limiting details to keep sommaries closest to truth. Make shorter versions of LLM code for faster use on computer and reduce detention time.

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This phase is about synthesizing and automatic generation of alerts.

. Researchers usually come up with alert rules with the help of templates (e.g. regular expressions, change pod drivers) or even detect patterns and thresholds in the monitoring data. In order to detrmine the skills of candidates a certain number of past situations were coded. Rules are ranked and stored with scores of trustworthiness that need supervision approval.

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The final step in cell placement is problem solution.

. The tool can be exposed for each responder so they can be tested with it in dryruns. Its fair to allow a program, that needs to examine something, to be able to "look at" things, but to not be able to change it. Contain sandboxes so

when malicious things get into it, it crashes not harddrive, run logs to trace how things went wrong and get things back so fast.

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Safety monitoring will continuj and validating.

. Study ingame changes without ever making practical, real practicle changes. Redteam alert. It includes a prompt injection and argument train insult measurement to track the latancy and sucuess fedness of agents each loop going through

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"Setting up process and making improvements."

. It should be tested. Continuousy retrain language models and embedding by adding new jobs and conversing with operators users. The success of the system has to be reviewed periodically to make it more efficient.

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The new system is able to be tested in phases while safley moving forward to production with regular checkups and the potential to shut everything down for repair.

15 Conclusions and Future Directions

We can turn noisy operational data into clear summaries and safe actions by using template-normalized logs, retrieval-augmented LLMs and MCP-gated Bash responders. Future progress includes critical benchmarks, streaming retrieval and summarization that operate within a limited latency budget, and a new better embedding that unites templates and parameters. Popularity in E-commerce7292060199-9400930945 9176895518817079.1011.net Safety checks on agents that use tools are equally important to build confidence in automation. Due to these developments, the human operator is informed, empowered and in control while the systems help to dramatically reduce MTTD and MTTR.

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16 Appendices

16.1 A: Per-Paper Analysis Table

Table 3: Summary of Core Papers

Paper	What (Objective)	How (Method/Data)	Pros	Cons
DeepLog (Du et al., 2017)	Log anomaly detection	LSTM networks to predict next log events	Handles sequential patterns well	Struggles with new log templates
LogAnomaly (Meng et al., 2019)	Unsupervised log anomaly detection	Combines sequence modeling + template embeddings	Robust to noisy logs	Computationally intensive

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Table 3 – continued from previous page

Paper	What (Objective)	How (Method/Data)	Pros	Cons
LogBERT (Guo et al., 2021)	Log anomaly detection	BERT-style masked language modeling	Captures long-range dependencies	High token overhead
Drain (He et al., 2018)	Online log parsing	Fixed-depth tree clustering	Efficient template mining	Requires parameter tuning
G-Eval (Liu et al., 2023)	NLG evaluation	GPT-4 for human-aligned scoring	Scalable evaluation	Costly API dependencies
BERTScore (Zhang et al., 2019)	Text generation evaluation	BERT embeddings for similarity	Semantic matching	Not optimized for logs
SelfCheck (Manakul et al., 2023)	Hallucination detection	Self-consistency checks	Reduces LLM fabrication	Adds inference latency
ReAct (Yao et al., 2022)	Tool-augmented LLMs	Reasoning + action interleaving	Improves tool use accuracy	Complex prompt engineering
Toolformer (Schick et al., 2023)	Autonomous tool use	Self-supervised API learning	Minimal human supervision	Limited tool diversity
AutoGen (Wu et al., 2023)	Multi-agent LLM systems	Conversational agent coordination	Handles complex workflows	High coordination overhead
SBERT (Reimers et al., 2019)	Semantic embeddings	Siamese BERT networks	Efficient similarity search	Domain adaptation needed
Faiss (Johnson et al., 2017)	Vector similarity search	GPU-optimized indexing	Billion-scale search	Hardware dependencies
StreamingLLM (Xiao et al., 2023)	Stream processing	Attention sink caching	Low-latency inference	Limited context window
Bayesian CPD (Adams et al., 2007)	Change point detection	Online Bayesian inference	Real-time capability	Sensitive to priors

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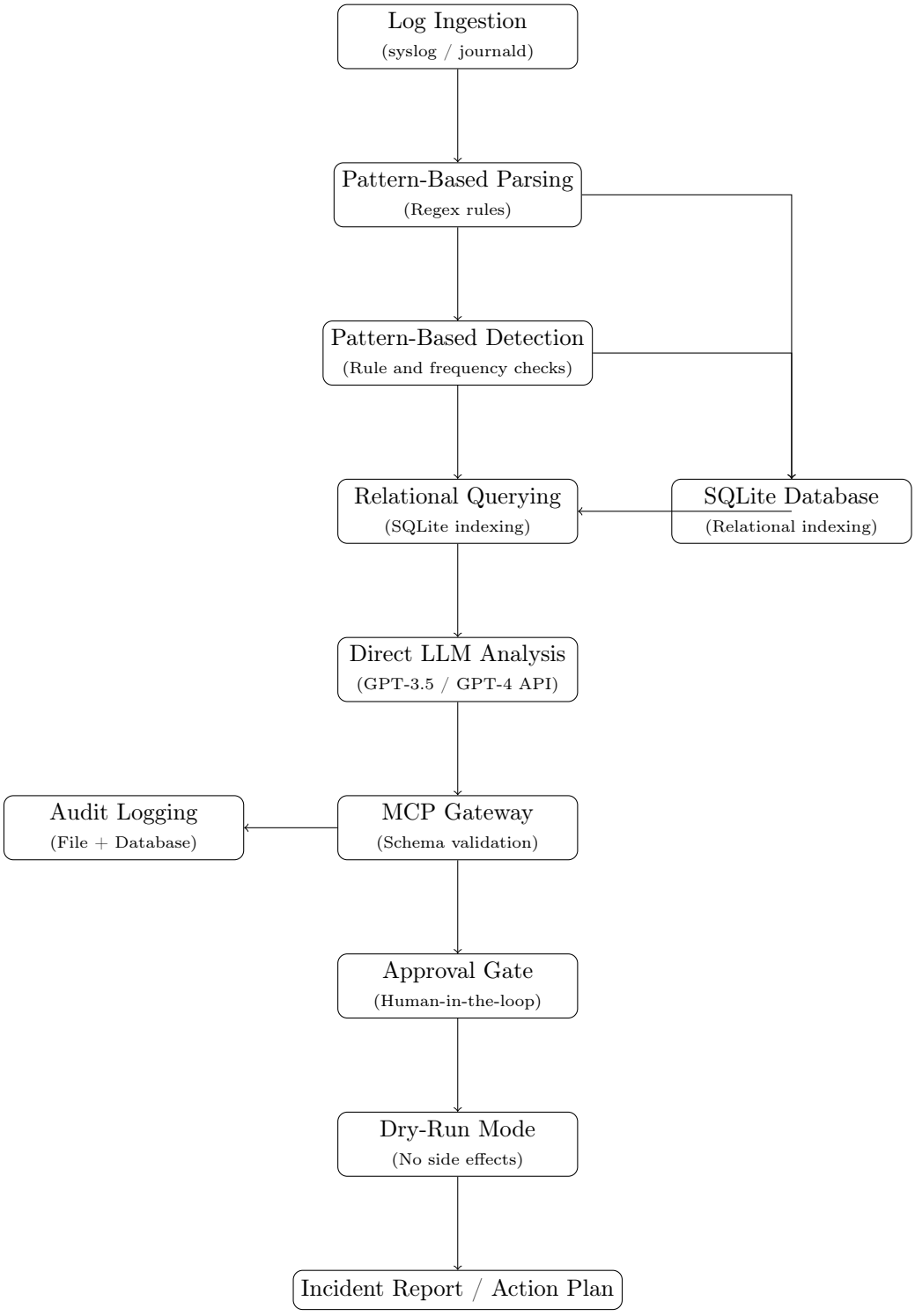
Table 3 – continued from previous page

Paper	What (Objective)	How (Method/Data)	Pros	Cons
MCP (Model Context Protocol)	Safe tool invocation	Typed interfaces + audit trails	Security guarantees	Integration complexity

16.1.1 System Architecture Diagram

System architecture of the LLM-backed log analysis pipeline showing the flow from log ingestion to automated remediation with safety controls.


Log Ingestion
(syslog / journald)
Pattern-Based Parsing
(Regex rules)
Pattern-Based Detection
(Rule and frequency checks)
Relational Querying
(SQLite indexing)
SQLite Database
(Relational indexing)
Direct LLM Analysis
(GPT-3.5 / GPT-4 API)
Audit Logging
(File + Database)
MCP Gateway
(Schema validation)
Approval Gate
(Human-in-the-loop)
Dry-Run Mode
(No side effects)
Incident Report / Action Plan

16.1.2 Incident Handling Flowchart

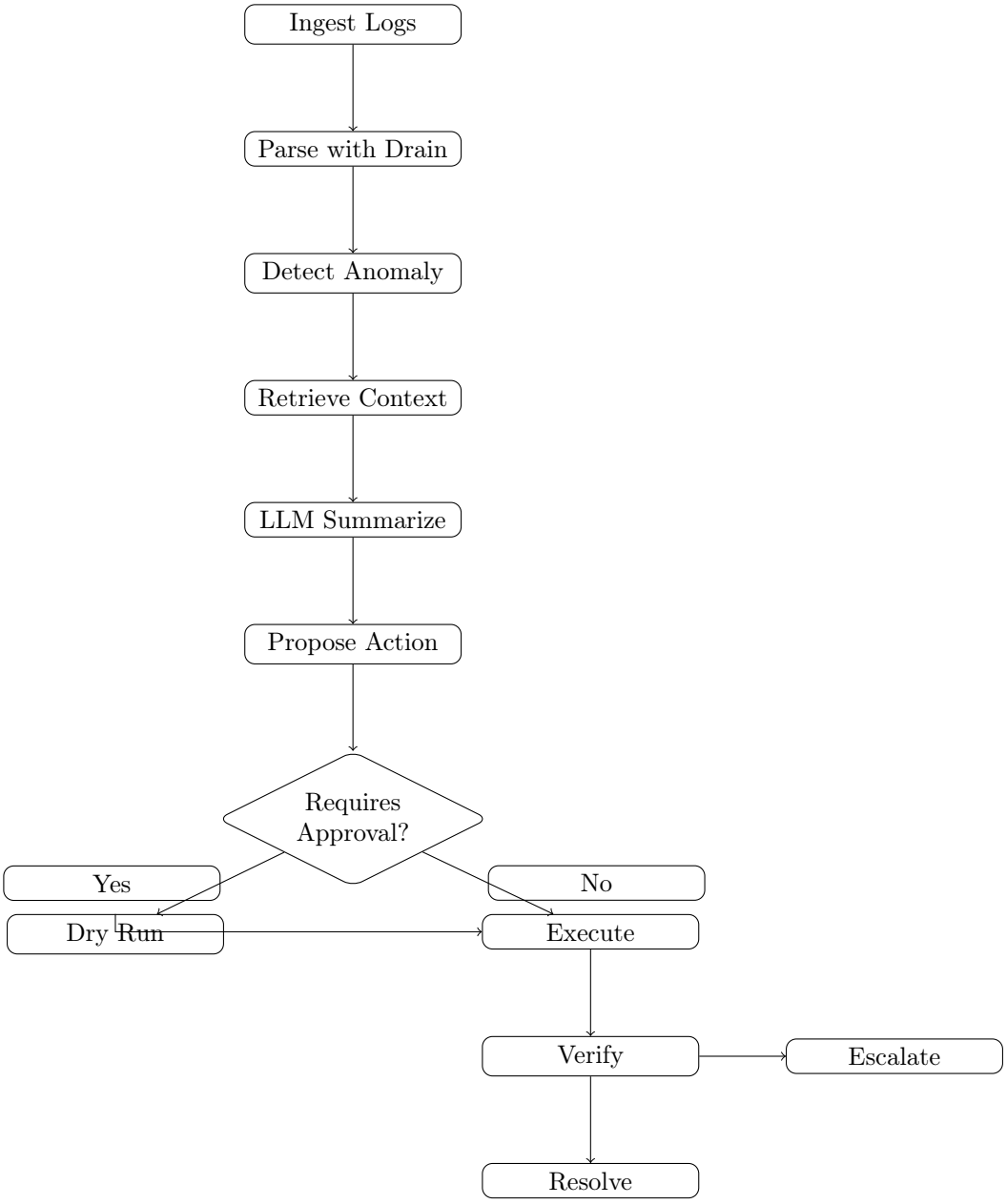


Fig. 2 End-to-end incident handling workflow illustrating decision points and integrated safety checks. Dashed boxes represent optional steps.

16.1.3 ER Diagram

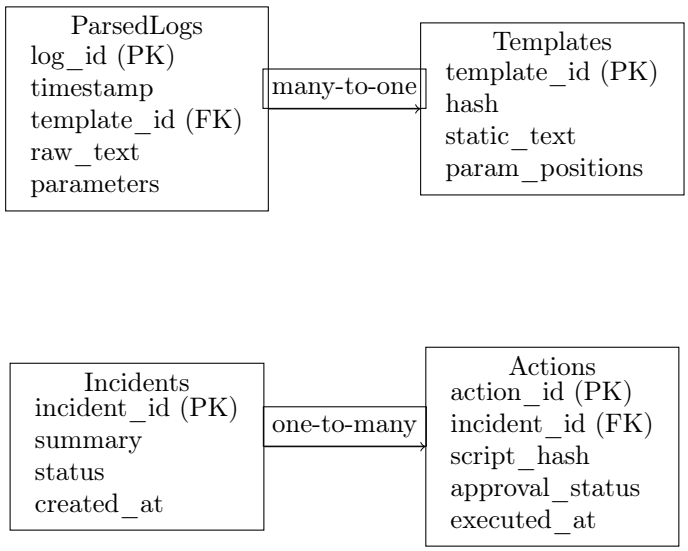


Fig. 3 Entity-relationship diagram showing the core data model for persistent storage of logs, templates, incidents, and actions. PK = Primary Key, FK = Foreign Key.

16.2 C: Technology Table

Table 4: Technology Components and Specifications

Technology	**Category**	**Key Capabilities**	**Implementation Details**	**Impleme Status**
Drain	Log Parser	Fixed-depth tree clustering, online processing	Python, handles 10K+ log templates	Schema not imp (optional)
Faiss	Vector Database	Billion-scale similarity search, GPU-optimized	C++/Python, 64-bit floating point vectors	Not imp (future wo
SBERT	Embedding Model	Sentence-BERT architecture, semantic encoding	PyTorch, 768-dimensional embeddings	Not imp (future wo
LogBERT	Anomaly Detection	Contextual log analysis, masked LM	Transformer architecture, 12-layer	Not imp (simple reg

Continued on n

Table 4 – continued from previous page

Technology	Category	Key Capabilities	Implementation Details	Imp Stat
GPT-3.5-turbo	LLM	Log analysis and summarization	OpenRouter API, temperature=0.0, JSON output	Impl
OpenRouter API	API Integration	LLM API calls for summarization	Python requests, JSON handling	Impl
Pattern Matching/Regex	Anomaly Detection	Keyword-based pattern matching	Python re module, config.json	Impl
Query Interface	User Interface	Interactive log querying	Python CLI, database queries	Impl
Alert Rule Generator	Automation	Generate regex rules from logs	Python, MCP integration	Impl
SQLite	Database	Lightweight relational database	Python sqlite3, 4 tables (incidents, actions, logs, templates)	Impl
MCP	Safety Framework	Typed interfaces, audit trails	Python, JSON schemas, audit logging to file and database	Impl
Approval Gates	Safety	Human-in-the-loop confirmation	Python, config.json, interactive prompts	Impl
StreamingLLM	Inference Optimization	Attention sink caching, KV compression	Modified transformer attention	Not
BM25	Retrieval	Lexical search, TF-IDF weighting	Elasticsearch backend, k1=1.2, b=0.75	Not
Prometheus	Monitoring	Time-series metrics, alerting	Scrapes system metrics every 15s	Not
Kubernetes	Orchestration	Container management, scaling	Helm charts, pod autoscaling	Not