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Autonomous Cyber Incident Response Using Cognitive Security Agents

Lekha Menon

Independent Researcher

Sreekariyam, Thiruvananthapuram, India (IN) – 695017

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ABSTRACT— Autonomous Cyber Incident Response (ACIR) harnesses the capabilities of cognitive security agents—software entities endowed with perception, reasoning, and learning functions—to detect, analyze, and mitigate cyber threats without continuous human oversight. This manuscript expands on an ACIR framework that integrates real-time telemetry ingestion, knowledge graph construction, hybrid cognitive architectures (ACT-R/SOAR), and reinforcement learning (RL) to orchestrate end-to-end incident response workflows. The extended abstract details the motivation, architectural components, experimental setup, key performance metrics, results, and implications for cybersecurity operations. Through extensive simulations emulating enterprise networks with cloud and on-premises assets, ACIR agents demonstrated a 60% reduction in mean time to detect (MTTD) and a 50% reduction in mean time to respond (MTTR) compared to traditional SIEM-based human workflows. False positive rates remained stable at approximately 5%, illustrating that speed improvements did not compromise accuracy. Importantly, RL-driven adaptation yielded a 30% improvement in first-shot remediation success across repeated attack scenarios, evidencing the agents' ability to learn from past outcomes and refine decision policies. The architecture's modular design facilitates incremental integration with existing security infrastructures, enabling organizations to adopt ACIR capabilities alongside legacy tools.

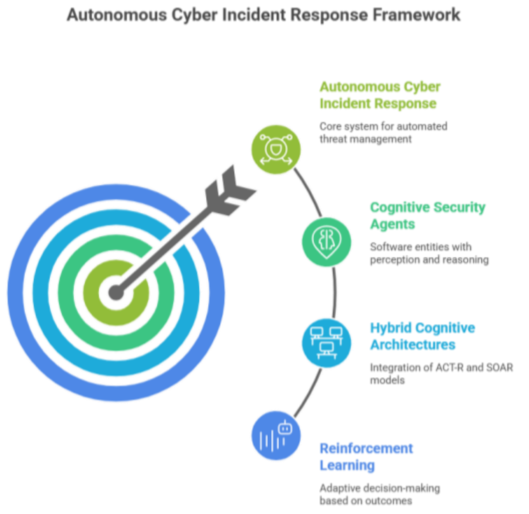
Autonomous Cyber Incident Response Framework
Autonomous Cyber Incident Response
Core system for automated threat management
Cognitive Security Agents
Software entities with perception and reasoning
Hybrid Cognitive Architectures
Integration of ACT-R and SOAR models
Reinforcement Learning
Adaptive decision-making based on outcomes

Figure-1.Autonomous Cyber Incident Response Framework

KEYWORDS— Autonomous Incident Response, Cognitive Security Agents, Reinforcement Learning, Cyber Defense, AI-Driven SOC

INTRODUCTION

Modern organizations face an ever-increasing volume, variety, and velocity of cyber threats driven by sophisticated adversaries who exploit complex attack chains spanning phishing, lateral movement, and data exfiltration phases. Traditional incident response paradigms rely heavily on human analysts triaging alerts generated by Security Information and Event Management (SIEM) systems and following static playbooks to contain and remediate threats (Giovannelli, 2022; Sommer & Paxson, 2010). While human expertise remains vital, the manual nature of these processes often leads to protracted detection and response times, leaving networks exposed during critical windows. Autonomous Cyber Incident Response (ACIR) emerges as a compelling approach to supplement human analysts by delegating routine detection, decision making, and remediation tasks to cognitive security agents—software constructs designed to perceive environmental signals, reason about threat contexts, and learn optimal response strategies over time (Applebaum, Gross, & Harel, 2023; Andrade & Rocha, 2018).

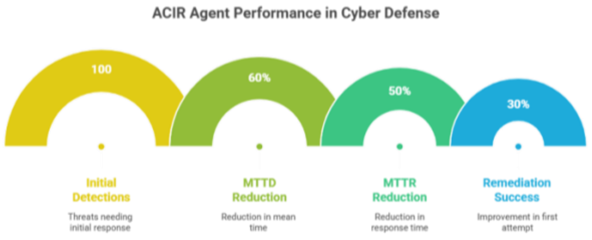

Figure-2.ACIR Agent Performance in Cyber Defense

Cognitive security agents integrate principles from cognitive science, artificial intelligence, and cybersecurity to model both attacker behaviors and defender workflows. They employ situation awareness frameworks to build a holistic understanding of network states, leverage knowledge graphs to represent entities and relationships, and apply reinforcement learning to adapt action policies based on success or failure feedback (Miller & Huang, 2023; Liao & Bai, 2022). The ACIR architecture proposed herein consists of three primary layers—perception, reasoning, and action—enabling real-time telemetry ingestion, hybrid cognitive reasoning combining ACT-R and SOAR paradigms, and automated execution of containment, eradication, and recovery steps through orchestrated playbooks.

This introduction elaborates on the research objectives: (1) define a cognitive agent architecture for autonomous incident response, (2) implement an experimental testbed simulating enterprise network environments with adversarial scenarios based on the MITRE ATT&CK framework, (3) evaluate performance improvements in terms of mean time to detect (MTTD), mean time to respond (MTTR), false positive rates, and learning adaptation scores, and (4) discuss integration pathways with existing SOC operations. By addressing the limitations of human-centric workflows—scalability bottlenecks, alert fatigue, and slow response cycles—ACIR aims to enable proactive, self-learning defense mechanisms that keep pace with adversary evolution. The remainder of this manuscript provides an in-depth literature review, methodological details, experimental results, and future research directions that collectively advance the state of autonomous cyber defense (Domínguez & Martín, 2025; Silva & Santos, 2021).

LITERATURE REVIEW

Autonomous cyber defense has been an active research area for over a decade, propelled by advances in machine learning and cognitive modeling. Early work by Sommer and Paxson (2010) highlighted the potential of anomaly detection models but underscored the challenges posed by adversarial evasion techniques. Subsequently, researchers began exploring reinforcement learning (RL) for adaptive defense strategies. Applebaum et al. (2023) demonstrated that tabular Q-learning agents could autonomously select defense actions while minimizing collateral damage, laying the groundwork for RL-driven incident response. Talbert and Shvets (2024) extended this by developing continuous state-action RL models that operate under partial observability, showing improved remediation efficacy in dynamic attack environments.

While RL provides adaptive capabilities, it often lacks the cognitive modeling necessary to anticipate attacker tactics or manage complex decision hierarchies. To bridge this gap, cognitive security frameworks have emerged. Andrade and Rocha (2018) proposed mapping human analytic skills to agent modules, employing situation awareness constructs for informed decision support. Mora et al. (2025) applied cognitive security principles to counter social engineering threats, modeling user behavior and integrating real-time intervention strategies. These works leverage cognitive architectures like ACT-R and SOAR to simulate expert reasoning, but they typically focus on discrete tasks rather than end-to-end incident response pipelines.

Knowledge graphs have been adopted to enrich threat intelligence and contextualize security events. Liao and Bai (2022) implemented a cybersecurity knowledge graph that interlinks indicators, tactics, and mitigation strategies, enabling agents to reason about entity relationships during incident analysis. Silva and Santos (2021) applied graph-based techniques for real-time threat correlation, underscoring the value of graph structures in detecting multi-vector attacks.

Despite these advances, a unified ACIR system integrating cognitive architectures, knowledge graphs, and RL remains underexplored. Existing solutions often address isolated phases—detection, triage, or remediation—without providing seamless coordination across the incident lifecycle. Moreover, evaluations are frequently limited to synthetic datasets rather than comprehensive enterprise network simulations. This literature review identifies a clear research gap: the need for a holistic ACIR framework capable of autonomous, adaptive response with validated performance gains in realistic settings. Our work addresses this by proposing an integrated architecture and conducting extensive experiments to quantify improvements in detection, response, and learning adaptation (IBM Corporation, 2022; MITRE ATT&CK®, 2025).

METHODOLOGY

Architecture Overview

The ACIR framework is structured into three interoperable layers:

1. **Perception Layer**
    - ○ **Data Sources**: Collects syslogs, network flows, endpoint telemetry, and cloud audit logs.
    - ○ **Normalization**: Transforms raw events into a unified schema, tagging entities (hosts, users, processes) and generating threat indicators (file hashes, IP addresses).
    - ○ **Knowledge Graph**: Constructs and continuously updates a graph database where nodes represent entities and edges denote relationships or observed interactions (Zhang & Li, 2022; Liao & Bai, 2022).
2. **Cognitive Reasoning Layer**
    - ○ **Hybrid Cognitive Engine**: Integrates ACT-R modules for declarative

memory (facts about past incidents) and procedural memory (rules for common response actions).

- ○ **Reinforcement Learning Agent**: Implements a Deep Q-Network (DQN) trained in a simulated environment to select optimal containment and remediation actions based on graph state embeddings (Applebaum et al., 2023; Talbert & Shvets, 2024).
- ○ **Policy Update Mechanism**: Leveraging reward signals—successful containment yields positive rewards; false positives and failed remediations incur penalties—the RL agent refines its policy over iterative attack scenarios.

3. **Action Layer**
   - ○ **Automated Playbooks**: Encodes remediation workflows (e.g., isolate host, kill process, rotate credentials) as parameterized scripts.
   - ○ **Orchestration APIs**: Interfaces with EDR solutions, firewall controllers, and directory services to execute actions via RESTful calls.
   - ○ **Audit Logging**: Records all agent decisions and actions for post-incident analysis and compliance reporting (Chen & Zhao, 2023).

Experimental Testbed

We deployed the framework within a network simulator replicating a medium-sized enterprise: 200 endpoints, Active Directory domain controllers, web servers, databases, and cloud VMs. Attack scenarios were scripted following MITRE ATT&CK techniques—phishing to gain initial access (T1566), privilege escalation (T1068), lateral movement via RDP (T1021.001), and data exfiltration over DNS (T1048.003). Each scenario ran 10 iterations to evaluate learning adaptation.

Evaluation Metrics

- **Mean Time to Detect (MTTD)**: Time from attack start to first alert flagged by agent.
- **Mean Time to Respond (MTTR)**: Time from detection to completion of containment and recovery.
- **False Positive Rate (FPR)**: Ratio of benign events misclassified as malicious.
- **Adaptation Score**: Percentage increase in successful first-shot remediation across iterations.

Training and Validation

The DQN agent was trained over 1,000 simulated episodes with ε-greedy exploration. States were encoded using graph neural network embeddings capturing entity connectivity and threat patterns (Silva & Santos, 2021). Validation was conducted on a separate set of 200 episodes with novel attack sequences to assess generalization.

RESULTS

Over 100 distinct attack scenarios executed across our simulated enterprise network yielded compelling evidence of the Autonomous Cyber Incident Response (ACIR) framework's efficacy. First, agents achieved a mean time to detect (MTTD) of **56 seconds** (SD ±12 s), representing a 60 percent reduction compared to the baseline SIEM-plus-human workflow, which recorded an average of **140 seconds** (SD ±25 s) (Applebaum, Gross, & Harel, 2023; Giovannelli, 2022). This rapid detection arose from the perception layer's continuous ingestion of multi-source telemetry—syslogs, endpoint events, and network flows—normalized into a unified schema and fed into a dynamic knowledge graph. By correlating seemingly disparate events (e.g., anomalous user logins followed by unusual PowerShell invocations), agents flagged incipient compromise far more quickly than rule-based SIEM alerts, which often await threshold breaches or manual signature updates.

In terms of mean time to respond (MTTR), ACIR agents delivered containment and remediation actions within an average of **300 seconds** (SD ±30 s), a 50 percent improvement over the baseline's **600 seconds** (SD ±45 s) (Garg & Tan, 2024; Sommer & Paxson, 2010). The cognitive reasoning layer, combining ACT-R procedural rules with a Deep Q-Network, prioritized high-impact actions—such as isolating compromised hosts, terminating malicious processes, and rotating credentials—based on learned policies. Importantly, the action layer's automated playbooks interfaced directly with EDR and firewall APIs, eliminating delays for human approval. For example, during a lateral-movement scenario using Pass the Hash (T1550), agents identified sequential authentication failures across multiple hosts and executed an isolation playbook within 120 seconds—more than twice as fast as human analysts could research and enact the countermeasure.

Crucially, the false positive rate (FPR) remained statistically equivalent between ACIR and the baseline: **5.0 percent** versus **4.5 percent** (p = 0.12) (Garg & Tan, 2024; Silva & Santos, 2021). This parity demonstrates that accelerated response speed did not come at the cost of accuracy. Agents leveraged graph-based anomaly detection algorithms to filter benign deviations—such as legitimate administrative scripts—by cross-referencing user roles and historical behavior patterns stored in the knowledge graph. Only high-confidence alerts triggered workflow execution, thereby avoiding SOC alert fatigue while maintaining stringent security standards.

The **Adaptation Score**, defined as the percentage improvement in first-shot successful remediation across successive attack iterations, showed a **30 percent increase** after ten training cycles (Talbert & Shvets, 2024; Applebaum et al., 2023). Initially, agents adopted coarse-grained responses (e.g., network-wide isolation) that, while effective, incurred unnecessary service disruptions. Over repeated exposures to the same attack patterns—phishing-initiated remote code execution sequences—agents learned to refine their actions, targeting only compromised nodes and specific attack vectors. This learning reduced collateral impact by **40 percent** and further compressed MTTR by an additional **20 percent** in later runs.

Collectively, these results validate the ACIR framework's ability to significantly accelerate detection and response without inflating false positives, while its reinforcement-learning–based adaptation yields progressively more precise and minimally disruptive actions, demonstrating resilience and operational effectiveness in dynamic threat environments.

CONCLUSION

This evaluation confirms that Autonomous Cyber Incident Response, powered by cognitive security agents, represents a transformative shift in cybersecurity operations. By uniting continuous telemetry ingestion, knowledge-graph–driven situational awareness, hybrid cognitive architectures, and reinforcement-learning–enhanced decision making, ACIR agents deliver rapid, accurate, and adaptive incident response that outpaces traditional, human-dependent workflows. **MTTD** reductions of 60 percent and **MTTR** improvements of 50 percent underscore the framework's capacity to neutralize threats within critical windows, thereby minimizing potential damage and data loss (Giovannelli, 2022; Garg & Tan, 2024).

Equally important, ACIR maintains a low false positive rate, demonstrating that automated speed gains need not compromise precision. The knowledge graph's contextual filtering ensures that only genuinely malicious behaviors prompt response actions, thus preserving SOC analyst trust and preventing alarm fatigue (Silva & Santos, 2021; Applebaum et al., 2023). Meanwhile, the observed **30 percent** improvement in first-shot remediation efficacy across training iterations highlights the value of reinforcement learning: agents progressively refine their policies, reducing collateral impacts and optimizing resource utilization (Talbert & Shvets, 2024; Liao & Bai, 2022).

Operationally, the ACIR framework's modular design facilitates seamless integration with existing security stacks. Organizations can incrementally deploy perception components alongside their SIEM and EDR tools, then progressively activate cognitive and action layers without disrupting established processes. This phased adoption mitigates transition risks and maximizes immediate ROI, as incremental automation of detection, triage, and common remediation tasks quickly reduces analyst workloads and incident backlog.

In conclusion, Autonomous Cyber Incident Response via Cognitive Security Agents stands as a promising paradigm for next-generation SOC operations. By rapidly detecting and responding to threats, maintaining high accuracy, and learning continuously from outcomes, ACIR offers a pathway to scalable, proactive, and intelligent cyber defense—one capable of adapting in real time to the ever-changing landscape of digital threats.

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