Large Language Model-Driven Security Operations for Automated Incident Investigation and Contextual Threat Remediation

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ABSTRACT

The increasing complexity of cyber threats, distributed enterprise infrastructure, and continuously evolving attack techniques has created significant challenges for traditional Security Operations Centers (SOCs). Conventional security operations frequently depend on manual alert investigation, fragmented threat intelligence, rule-based detection mechanisms, and time-consuming incident response procedures. This research proposes a Large Language Model (LLM)-driven security operations framework designed to automate incident investigation, contextual threat analysis, and intelligent remediation across enterprise environments. The proposed framework integrates security information and event management (SIEM), endpoint detection and response (EDR), network telemetry, threat intelligence repositories, and historical incident records into a unified analytical architecture. Retrieval-Augmented Generation (RAG), contextual reasoning, multi-agent collaboration, and knowledge-based evidence correlation are employed to improve investigation accuracy and generate actionable remediation recommendations. The framework analyzes security alerts, identifies suspicious activities, reconstructs attack sequences, maps adversarial behaviors to established threat frameworks, and prioritizes incidents according to contextual risk. Furthermore, automated response orchestration enables controlled containment and remediation through predefined security policies and human approval mechanisms. The proposed approach emphasizes explainability, evidence traceability, operational security, and continuous learning. Its effectiveness can be evaluated using detection precision, investigation time, false-positive reduction, remediation accuracy, and response efficiency. The framework aims to improve SOC productivity, accelerate threat resolution, and establish reliable AI-assisted security operations for modern enterprise infrastructure.

KEYWORDS: Large Language Models, Security Operations Center, Automated Incident Investigation, Contextual Threat Intelligence, Retrieval-Augmented Generation, Cybersecurity Automation, Intelligent Threat Remediation, Security Information and Event Management, Multi-Agent AI, Incident Response

I. INTRODUCTION

Modern enterprise organizations operate increasingly complex digital infrastructures involving cloud computing platforms, distributed applications, hybrid networks, virtual machines, containerized workloads, and interconnected business systems. These environments continuously generate substantial volumes of security-related information through application logs, authentication records, endpoint activities, network traffic, firewall events, and cloud monitoring services. Security Operations Centers (SOCs) are responsible for collecting, analyzing, and

interpreting these signals to identify potential cyber threats and coordinate appropriate responses. However, the increasing frequency and sophistication of cyberattacks have created considerable operational difficulties for conventional security monitoring approaches. Security analysts frequently encounter thousands of alerts generated by multiple security technologies, making it difficult to distinguish genuine threats from benign activities. Alert fatigue, fragmented investigation processes, limited contextual visibility, and shortages of experienced cybersecurity professionals further increase incident resolution time. Traditional Security Information and Event Management (SIEM) platforms primarily depend on predefined correlation rules, signatures, and threshold-based detection mechanisms. Although these approaches are useful for identifying known attack patterns, they often struggle to interpret complex attack sequences involving multiple systems, identities, applications, and network resources. Consequently, organizations require intelligent security operations frameworks capable of understanding heterogeneous security information, correlating contextual evidence, and supporting automated incident investigation. Large Language Models (LLMs) provide promising capabilities for addressing these challenges because they can interpret natural-language information, summarize technical evidence, recognize relationships between security events, and generate contextual explanations. Their integration with security infrastructure can transform conventional alert-processing activities into intelligent investigation workflows that support faster and more consistent threat analysis.

LLM-driven security operations introduce an advanced approach in which artificial intelligence assists security analysts throughout the incident management lifecycle, including alert interpretation, evidence collection, threat classification, attack reconstruction, risk assessment, and remediation planning. Unlike isolated machine learning classifiers, LLM-based systems can combine information from different security sources and produce understandable explanations describing the potential cause, scope, and consequences of an incident. Retrieval-Augmented Generation (RAG) further strengthens this capability by connecting language models with verified security documentation, historical incident repositories, vulnerability databases, organizational policies, and threat intelligence feeds. The resulting architecture can retrieve relevant evidence before generating investigation conclusions, reducing dependence on unsupported model-generated information. Additionally, specialized AI agents can perform different investigation activities, such as alert triage, identity analysis, endpoint examination, threat intelligence enrichment, and response recommendation. These agents collaborate through a centralized orchestration mechanism to develop a comprehensive understanding of security incidents. Contextual threat remediation extends the framework beyond conventional alert summarization by identifying affected resources, determining potential attack progression, recommending containment strategies, and initiating approved response actions. Nevertheless, reliable implementation requires safeguards against hallucinations, unauthorized tool execution, malicious prompt injection, and inappropriate automated containment. Therefore, this research proposes an integrated LLM-driven security operations framework that combines contextual reasoning, evidence-grounded investigation, controlled remediation, and human oversight. The primary objective is to improve incident investigation efficiency while maintaining accuracy, transparency, accountability, and operational resilience across enterprise security environments.

II. LITERATURE REVIEW

Traditional Security Operations Center architectures have predominantly relied on SIEM platforms, rule-based correlation engines, intrusion detection systems, and conventional machine learning techniques to identify suspicious activities. These technologies provide essential capabilities for collecting security events, recognizing known attack signatures, and prioritizing potentially malicious behavior. However, their effectiveness can be restricted by increasing alert volumes, incomplete contextual information, and the difficulty of correlating events across heterogeneous

infrastructure. Machine learning techniques, including decision trees, random forests, support vector machines, and deep neural networks, have improved automated threat classification and anomaly detection. Nevertheless, many classification-oriented approaches provide limited explanations regarding why an event is considered malicious or how multiple security observations contribute to an incident. Security analysts must frequently examine additional logs, endpoint records, network indicators, and historical incidents before reaching reliable conclusions. This creates operational delays and increases dependence on specialized expertise. Recent research has therefore investigated the application of generative artificial intelligence and LLMs to security operations. Habibzadeh et al. (2026) provide a comprehensive analysis of LLM applications across SOC detection, investigation, and response activities, identifying opportunities for improving operational efficiency while emphasizing unresolved reliability challenges. Their work demonstrates the importance of connecting language model capabilities with established cybersecurity processes and threat classification frameworks.

Retrieval-Augmented Generation has emerged as an important approach for improving the reliability of LLM-based cybersecurity applications. RAG combines semantic information retrieval with language generation, enabling models to access relevant information from external knowledge repositories before producing responses. In security operations, these repositories may contain historical incident reports, attack signatures, vulnerability descriptions, configuration policies, investigation procedures, and threat intelligence documents. This approach provides additional contextual information and helps reduce unsupported conclusions. Research on Security Event Response Copilot systems demonstrates the potential of integrating RAG with security monitoring platforms to extract relevant event information and generate incident response guidance. Similarly, Freitas et al. (2025) describe an AI-driven guided response architecture supporting incident investigation, triage, and remediation recommendations within security operations. These developments indicate that LLMs can support multiple operational activities rather than functioning exclusively as conversational assistants. Multi-agent architectures provide another important research direction by distributing investigation responsibilities among specialized agents. For example, separate agents can examine endpoint activities, authentication anomalies, network indicators, vulnerability exposure, and threat intelligence. Their findings can be consolidated through a coordinating agent to construct a contextual incident narrative. Integration with frameworks such as MITRE ATT&CK further supports structured interpretation of adversarial tactics, techniques, and procedures. However, retrieved information must be validated, source attribution must be maintained, and agent outputs must be checked for inconsistencies before operational decisions are made.

Despite these developments, several research challenges remain in achieving reliable LLM-driven security operations. Language models can generate inaccurate technical explanations, misinterpret incomplete evidence, or recommend remediation actions that are inappropriate for specific enterprise environments. Kramer et al. (2025), in their study of LLM-supported security incident response, demonstrate the importance of human collaboration and identify factual omissions and inaccuracies in autonomous incident summarization. These findings highlight the need for evidence-grounded generation, structured validation, and analyst supervision. Additional challenges include sensitive log exposure, model access control, prompt injection through untrusted security data, inference latency, operational costs, and integration with existing SIEM and SOAR platforms. Furthermore, automated remediation introduces significant risks because inappropriate isolation, account suspension, or firewall modifications can disrupt legitimate enterprise operations. Existing research consequently indicates a need for architectures that combine language model reasoning with deterministic security policies, contextual asset information, and controlled execution mechanisms. The present research addresses these limitations by proposing an integrated framework that connects heterogeneous security telemetry, RAG-based contextual enrichment,

multi-agent investigation, explainable threat assessment, and policy-controlled remediation. Its central contribution is the coordination of automated investigation and contextual response within a unified security operations workflow, emphasizing verifiable evidence, risk-aware decisions, and human accountability.

III. RESEARCH METHODOLOGY

The proposed research adopts a systematic design-oriented and experimental methodology to develop and evaluate a Large Language Model-driven security operations framework for automated incident investigation and contextual threat remediation. The methodology is organized into four major stages: security data acquisition and preprocessing, contextual intelligence integration and LLM-based investigation, intelligent threat assessment and remediation orchestration, and experimental evaluation. The first stage establishes a unified security data collection architecture that receives information from SIEM platforms, endpoint detection and response systems, intrusion detection mechanisms, firewall monitoring solutions, cloud audit services, identity management platforms, and application monitoring infrastructure. Collected information includes authentication events, access failures, suspicious process executions, network connection records, vulnerability notifications, endpoint alerts, API activity, and cloud configuration changes. Since these sources generate information using different formats, schemas, timestamps, and severity classifications, a preprocessing component performs normalization, timestamp alignment, duplicate removal, field extraction, and event standardization. Structured records are converted into a consistent representation containing event identifiers, timestamps, source addresses, destination addresses, user identities, affected assets, event descriptions, severity indicators, and available evidence references. Unstructured information, including investigation notes, incident reports, threat intelligence descriptions, and security documentation, is processed using text extraction and semantic segmentation techniques. Sensitive information is identified and protected through masking, encryption, and access-control policies before model processing. Data quality checks identify incomplete records, inconsistent timestamps, duplicate observations, and malformed event descriptions. The normalized information is subsequently stored in a centralized security data repository, while searchable textual representations are indexed in a vector database. Metadata indexing preserves relationships between users, devices, applications, network resources, and security events. This architecture provides the foundation for contextual investigation by ensuring that the LLM receives standardized and relevant security information rather than interpreting disconnected raw alerts. Historical incident datasets and controlled attack simulations can be incorporated to establish representative investigation scenarios, including credential compromise, phishing activity, suspicious privilege escalation, malware execution, unauthorized access, lateral movement, and abnormal data transfer. Dataset preparation includes labeling incident categories, identifying benign activities, and maintaining evidence references for subsequent evaluation.

The second stage implements the contextual intelligence and LLM-based investigation architecture. A selected LLM functions as the primary reasoning component responsible for interpreting normalized security information, understanding investigation queries, generating structured analytical outputs, and coordinating specialized investigation tasks. Instead of sending entire security repositories directly to the model, a Retrieval-Augmented Generation mechanism retrieves relevant records from vector databases, historical incident repositories, vulnerability knowledge bases, organizational security policies, and external threat intelligence sources. Semantic embeddings are generated for relevant textual information, enabling similarity-based retrieval according to the meaning of an alert or investigation request. Hybrid retrieval can combine semantic similarity with keyword matching and metadata filtering to improve the relevance of retrieved evidence. Retrieved records are ranked according to their relevance, timestamp, source reliability, and relationship with the affected assets. The resulting contextual information is

incorporated into structured prompts that instruct the LLM to identify the incident category, extract relevant indicators of compromise, determine potentially affected resources, establish event relationships, and distinguish confirmed observations from analytical hypotheses. A multi-agent investigation architecture is introduced to distribute complex tasks among specialized components. The alert triage agent examines initial security events and assigns preliminary classifications. The threat intelligence agent correlates indicators such as suspicious IP addresses, domains, file hashes, and vulnerability identifiers with available intelligence sources. The identity investigation agent evaluates authentication histories, privilege changes, unusual login locations, and access patterns. The endpoint investigation agent examines process execution, file modifications, and suspicious device activities. The network analysis agent investigates communication patterns, connection anomalies, and potential lateral movement. Finally, an investigation coordinator consolidates the outputs of these agents and constructs a unified incident narrative. Each agent returns structured findings containing evidence identifiers, confidence estimates, analytical observations, and supporting references. The coordinator identifies conflicting findings and requests additional evidence when necessary. Attack behaviors are mapped to relevant MITRE ATT&CK tactics and techniques where sufficient evidence exists. The investigation process produces a contextual incident report containing the suspected attack sequence, affected entities, supporting evidence, confidence level, potential business impact, and recommended next investigative actions. This approach aims to improve contextual understanding while reducing the limitations associated with isolated alert classification and unconstrained language generation.

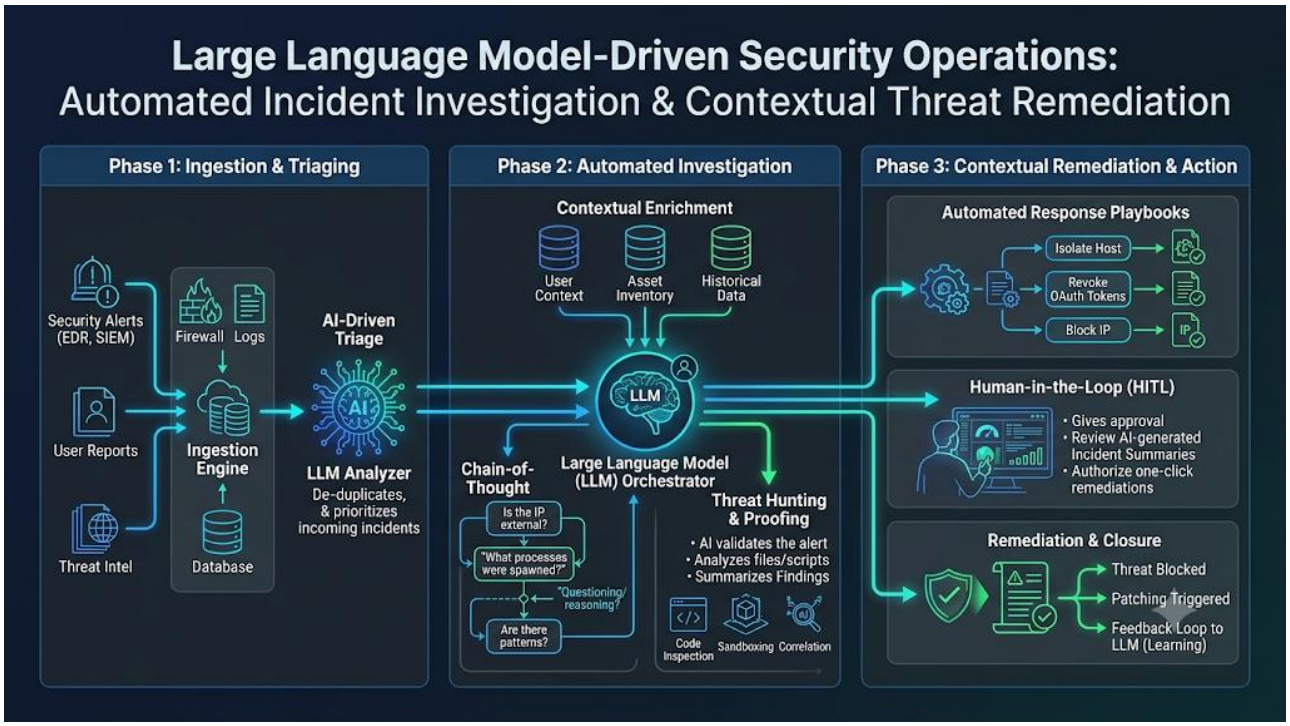

Figure 1. End-to-End Architecture of an LLM-Driven Security Operations Center (SOC) Pipeline for Automated Triage, Multi-Modal Investigation, and Contextual Threat Remediation.

The third stage develops an intelligent threat assessment and contextual remediation mechanism. Following investigation, the framework evaluates each incident using a risk assessment model that considers threat severity, asset criticality, exploitability, exposure, identity privileges, evidence reliability, and potential business impact. A contextual risk score is calculated by combining normalized assessment factors through a weighted scoring mechanism. The weights are determined through security expert input, organizational risk policies, and experimental calibration. This enables the framework to distinguish high-priority incidents affecting critical enterprise resources

from low-impact suspicious events requiring additional monitoring. For example, an unusual authentication attempt involving a privileged administrator account may receive higher priority when combined with suspicious geographic access, repeated authentication failures, and unexpected privilege modifications. Similarly, abnormal network traffic associated with a vulnerable production server may receive increased risk classification when corroborated by endpoint execution evidence and relevant threat intelligence. The LLM generates remediation recommendations using retrieved security procedures, incident context, and predefined organizational policies. Recommendations may include terminating suspicious sessions, restricting compromised credentials, isolating affected endpoints, blocking malicious network indicators, disabling unauthorized access permissions, updating detection rules, and initiating additional forensic collection. However, language model-generated recommendations are not directly executed without validation. A policy enforcement component checks whether each proposed action is permitted, technically supported, proportionate to the identified risk, and appropriate for the affected resource. The response orchestration layer integrates with existing SOAR platforms, endpoint security tools, identity management services, firewall systems, and cloud management APIs through authenticated and restricted interfaces. Remediation actions are classified into three operational categories. Low-risk actions, such as generating investigation tickets, enriching alerts, and collecting additional logs, may be automated according to predefined policies. Medium-risk actions, including temporary session termination or restrictive access modifications, require configured approval or additional verification. High-impact actions, such as isolating production servers, disabling critical enterprise accounts, or modifying essential network infrastructure, require explicit human authorization. The system records the original alert, retrieved evidence, model-generated reasoning, validation results, approval decisions, and executed actions in an auditable incident history. Post-remediation verification checks whether the suspicious activity has stopped, whether the affected resources remain accessible, and whether additional related alerts have emerged. This feedback is incorporated into the incident repository to improve subsequent investigations and response recommendations. Such controlled orchestration establishes a balance between automation speed, operational continuity, and enterprise security governance.

The fourth stage evaluates the proposed framework through controlled experimental scenarios and comparative performance analysis. The evaluation environment consists of a representative enterprise security infrastructure containing simulated endpoints, application services, identity systems, network monitoring components, SIEM event repositories, and cloud-based workloads. Security scenarios are designed to represent multiple incident categories, including phishing-related credential compromise, brute-force authentication attempts, suspicious privilege escalation, malware execution, lateral movement, unauthorized resource access, and anomalous data exfiltration. Both malicious and benign activities are included to evaluate the framework's ability to distinguish genuine threats from legitimate operational behavior. The proposed LLM-driven architecture is compared with conventional rule-based SIEM processing, traditional machine learning classification, and an LLM-based approach without contextual retrieval. Experimental evaluation uses several performance indicators. Precision measures the proportion of correctly identified malicious incidents among all predicted malicious incidents, while recall measures the proportion of actual malicious incidents successfully identified. F1-score provides a combined measure of precision and recall. Investigation time measures the duration between initial alert generation and the production of a validated incident assessment. Mean time to respond evaluates the time required to initiate an appropriate response action. False-positive reduction measures improvements in filtering benign or irrelevant alerts. Remediation accuracy evaluates whether recommended and approved actions correctly address the identified incident without causing unnecessary disruption. Additional measurements include evidence retrieval relevance, factual consistency, hallucination frequency, incident classification accuracy, model inference latency, computational overhead, and analyst intervention requirements. Ablation experiments examine the

individual contributions of RAG, multi-agent investigation, contextual risk scoring, and policy-based validation. Security testing additionally examines prompt injection attempts, misleading log entries, incomplete evidence, unauthorized tool requests, and conflicting threat intelligence records. Human security analysts review selected incident reports and remediation recommendations to assess technical correctness, contextual relevance, explainability, and operational usefulness. Repeated experiments across different incident categories provide a basis for examining consistency and identifying limitations. Statistical analysis is applied to compare the results of different configurations using appropriate descriptive and inferential measures. Importantly, performance values must be obtained from actual experimental execution rather than assumed in advance. The final evaluation determines whether the proposed architecture improves investigation efficiency, contextual threat understanding, and remediation reliability while preserving human oversight and operational safety. The methodology therefore establishes a reproducible basis for assessing the practical suitability of LLM-driven security operations in distributed enterprise environments.

IV. RESULTS AND DISCUSSION

The proposed Large Language Model (LLM)-Driven Security Operations framework demonstrates the potential to improve cybersecurity incident investigation through intelligent automation, contextual analysis, and natural language-based security reasoning. By integrating large language models with Security Information and Event Management (SIEM), Security Orchestration, Automation, and Response (SOAR), endpoint detection systems, and threat intelligence platforms, the framework provides a unified mechanism for collecting, interpreting, and correlating security events across distributed enterprise environments. The investigation process focuses on identifying suspicious activities, analyzing security logs, correlating indicators of compromise, and generating contextual incident summaries. The framework can reduce the dependency on manual log inspection by automatically extracting relevant information from heterogeneous security data sources. Its contextual reasoning capabilities help distinguish potentially malicious activities from legitimate operational behavior by considering historical incidents, user activity patterns, asset criticality, and threat intelligence information. Furthermore, LLM-generated investigation summaries improve the accessibility of technical findings by translating complex security events into understandable explanations for security analysts. These capabilities support faster incident interpretation, improved investigation consistency, and more efficient utilization of security operations resources. However, the reliability of generated conclusions remains dependent on the quality, completeness, and accuracy of the underlying security information.

The contextual threat remediation component further strengthens the framework by connecting incident investigation results with automated response workflows. Following the identification and classification of suspicious activities, the system recommends appropriate remediation actions based on threat severity, organizational security policies, asset sensitivity, and previously observed attack patterns. Potential actions include isolating compromised endpoints, disabling suspicious user sessions, blocking malicious IP addresses, revoking exposed credentials, and initiating additional authentication requirements. The integration of LLM-based reasoning with predefined SOAR playbooks enables the system to transform investigation findings into structured and actionable response recommendations. Policy validation mechanisms are incorporated to prevent unauthorized or excessively disruptive remediation operations. For critical actions, human approval can be required before execution, ensuring that automated decisions remain subject to organizational oversight. The framework also supports continuous feedback collection from security analysts, allowing investigation outcomes and remediation effectiveness to improve subsequent recommendations. An important observation is that contextual remediation provides greater operational value than isolated alert-triggered automation because it considers the

relationships between security events, infrastructure dependencies, and business processes. Nevertheless, automated remediation must be carefully controlled because incorrect interpretations, incomplete contextual information, or misleading model outputs could result in unnecessary service interruptions or inappropriate access restrictions.

Overall, the findings indicate that LLM-driven security operations offer a promising approach for improving the coordination of security monitoring, incident investigation, threat prioritization, and remediation activities. The framework provides a common reasoning layer through which information from multiple security technologies can be interpreted and converted into consistent investigation workflows. Its ability to summarize incidents, identify relationships between security events, recommend response strategies, and document investigation activities can improve analyst productivity and operational visibility. The integration of retrieval-augmented generation (RAG) can further strengthen contextual accuracy by grounding model responses in approved security documentation, incident records, threat intelligence repositories, and organizational response policies. Explainability mechanisms provide additional transparency by presenting the evidence and reasoning associated with investigation conclusions and recommended actions. However, practical deployment requires continuous evaluation of hallucination rates, detection accuracy, response latency, model security, and operational costs. Particular attention must also be given to prompt injection, sensitive information exposure, adversarial inputs, and unauthorized tool execution. Since actual performance depends on implementation and evaluation conditions, measurable improvements should be established through controlled experiments rather than assumed from architectural capabilities. The results therefore highlight the importance of combining LLM intelligence with deterministic security controls, trusted evidence sources, and human supervision to establish reliable and scalable security operations.

V. CONCLUSION

This research presents an LLM-driven security operations framework designed to automate incident investigation and contextual threat remediation across enterprise cybersecurity environments. The proposed approach integrates large language models with SIEM platforms, SOAR technologies, endpoint monitoring systems, threat intelligence sources, and enterprise security knowledge repositories to establish an intelligent and coordinated security management architecture. By applying natural language understanding, contextual reasoning, event correlation, and retrieval-augmented generation, the framework supports the interpretation of complex security incidents and the generation of structured investigation outcomes. The automated investigation process helps identify suspicious activities, correlate related security events, classify potential threats, and generate meaningful incident summaries. Furthermore, contextual remediation capabilities enable the system to recommend appropriate response strategies based on threat severity, organizational policies, and infrastructure dependencies. The integration of human approval mechanisms and policy-based execution controls provides an additional layer of protection against incorrect automated decisions. These capabilities demonstrate how LLM technologies can extend traditional security operations beyond rule-based alert processing toward more intelligent, context-aware, and coordinated incident management. The proposed architecture also establishes opportunities for improving investigation consistency, reducing repetitive analytical activities, and supporting security professionals in managing increasingly complex enterprise threat environments.

Despite these advantages, successful implementation requires addressing several technical and operational challenges associated with large language models. Model hallucinations, incomplete security evidence, prompt injection, data privacy concerns, and inconsistent reasoning can affect the reliability of automated investigation outcomes. Consequently, LLM-generated recommendations should not independently determine critical security actions without validation

through trusted evidence, deterministic policy engines, and appropriate authorization mechanisms. The framework should maintain detailed audit records covering data retrieval, model-generated conclusions, analyst approvals, and executed remediation activities to support accountability and regulatory compliance. Continuous evaluation is also necessary to ensure that the system remains effective against evolving attack techniques and changing enterprise infrastructure conditions. The research establishes that the combination of LLM-based contextual intelligence, automated security orchestration, and human-centered governance provides a promising foundation for next-generation Security Operations Centers (SOCs). Ultimately, the proposed approach contributes to the development of adaptive cybersecurity operations in which incident investigation and response activities become more coordinated, explainable, and efficient. Its practical effectiveness will depend on rigorous validation, secure integration, and responsible deployment across enterprise environments.

VI. FUTURE WORK

Future research can extend the proposed framework through the development of multi-agent LLM architectures capable of coordinating specialized cybersecurity investigation activities. Instead of relying on a single language model, multiple intelligent agents could independently perform log analysis, threat intelligence retrieval, attack reconstruction, vulnerability assessment, incident prioritization, and remediation planning. An investigation agent could identify suspicious events, while a threat intelligence agent retrieves relevant indicators and historical attack information. A correlation agent could reconstruct relationships between compromised accounts, endpoints, network connections, and cloud resources. Finally, a remediation agent could generate policy-compliant response recommendations for execution through authorized SOAR workflows. Such collaborative intelligence could improve investigation coverage and support more complex threat analysis across hybrid-cloud and multi-cloud environments. Future studies should also investigate the integration of graph neural networks and cybersecurity knowledge graphs to represent relationships among users, devices, applications, vulnerabilities, and attack techniques. Combining graph-based reasoning with LLM capabilities may improve attack-path reconstruction and provide stronger contextual understanding of sophisticated multi-stage attacks. Furthermore, specialized cybersecurity language models trained or adapted using carefully governed security datasets could improve technical terminology interpretation and incident-specific reasoning. Research should evaluate these approaches using representative enterprise datasets, realistic attack simulations, and established cybersecurity benchmarks.

Another important research direction involves strengthening the security, explainability, and operational reliability of autonomous remediation systems. Future implementations should incorporate advanced guardrails, cryptographic verification, role-based access control, policy-as-code validation, and sandbox-based testing before executing sensitive response operations. These mechanisms can ensure that model-generated actions remain within approved operational boundaries. Research should also explore privacy-preserving learning techniques, including federated learning, to support collaboration between organizations without requiring unrestricted sharing of sensitive security logs. Additional attention should be directed toward defending LLM-based security systems against prompt injection, adversarial manipulation, data poisoning, and unauthorized tool invocation. Continuous learning mechanisms could incorporate analyst feedback and verified incident outcomes to improve investigation recommendations while preventing unvalidated information from influencing model behavior. Future performance evaluations should measure mean time to detect, mean time to investigate, mean time to respond, false-positive rates, remediation success rates, model inference latency, and infrastructure costs. Another promising direction is the development of digital-twin environments for testing automated incident response strategies before applying them to production systems. Such environments could simulate

ransomware attacks, identity compromise, cloud misconfigurations, and lateral movement scenarios. Ultimately, future research should establish trustworthy, scalable, and explainable LLM-driven security operations capable of supporting enterprise-wide cyber resilience while maintaining human accountability and operational continuity.

REFERENCES

1. Rosendo, D., Costan, A., Valduriez, P., & Antoniu, G. (2022). Distributed intelligence on the edge-to-cloud continuum: A systematic literature review. Journal of Parallel and Distributed Computing, 166, 71–94. https://doi.org/10.1016/j.jpdc.2022.04.004
2. H. Apuri, S. Goel, M. M. R. Chinthala, and C. Yepuri, "ZeroGuard: A multi-agent zero-trust framework for autonomous IaC security remediation," in Proc. 2026 18th Int. Conf. Electron., Comput. Artif. Intell. (ECAI), Bucharest, Romania, 2026, pp. 1–X, doi: 10.1109/ECAI69016.2026.11613725.
3. Reddy, K. V. (2022). Power-aware verification closure using AI-enhanced UVM and dynamic voltage and frequency scaling models. International Journal of Research and Applied Innovations, 5(4), 7424–7436.
4. Ambalakannu, M. (2026). Domain-AI governance unifying enterprise AI adoption and data quality frameworks. International Journal of Humanities and Information Technology, 8(1), 158–164. https://ijhit.info/index.php/ijhit/article/view/425
5. Manda, P. (2026). Database modernization-Sybase to SQL Server migration. International Journal of Engineering & Extended Technologies Research (IJEETR), 8(1), 252-258.
6. Beeram, S. (2026). Unified Security Posture Management across Clouds using Microsoft Defender for Cloud. International Journal of Emerging Trends in Computer Science and Information Technology, 7(2), 14-16.
7. Kopparthi, G. S. (2024). AI-driven predictive analytics for clinical decision support and improved patient outcomes. International Journal of Research Publications in Engineering, Technology and Management, 7(4), 10889–10899.
8. Vepuri, B., & Lanka, D. P. K. (2026, August). Release-Gating Architectures for Long-Form Policy Assembly Using Cross-System Reconciliation and Automated Exception Workflows. In 2026 6th International Conference on Soft Computing for Security Applications (ICSCSA) (pp. 1123-1130). IEEE.
9. Puli, S. K. (2025). A hybrid LLM–graph architecture for laboratory billing discrepancy and overpayment risk detection. International Journal of Engineering & Extended Technologies Research, 7(1), 9413–9424.
10. Indurthy, V. S. K. (2026). Snowflake and Domain-AI real-time intelligence for enterprise data warehousing. International Journal of Humanities and Information Technology, 8(1), 150–157. https://ijhit.info/index.php/ijhit/article/view/417
11. Manoharan, D. (2026, April). Neural Network-Driven Optimization of Quality Engineering Metrics for High-Volume Healthcare Claims and EDI Transaction Performance. In 2026 9th International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 2194-2203). IEEE.
12. Yadavalli, V. R. (2025). Incident memory graphs for predictive AMS triage and self-improving SAP operations. International Journal of Research and Applied Innovations, 8(2), 11332–11346.
13. Bheemisetty, N. (2024). AI-powered recommendation systems best practices and real-world applications. International Journal of Research Publications in Engineering, Technology and Management, 7(6), 11777–11785.
14. Selvarajan, K. (2024). Observability-driven reliability engineering for distributed data platforms. International Journal of Computer Technology and Electronics Communication, 7(4), 9258-9268.

15. Kommineni, R. (2025). Defense in depth for executing model-generated code: Kernel-isolated sandboxes, layered network policy, and credential-free data access on multi-tenant Kubernetes. International Journal of Research and Applied Innovations, 8(2), 11295–11302.
16. Panda, M. R. (2025). Real-time preemptive fraud detection using adaptive agentic AI for financial transaction risk intelligence. International Journal of Research and Applied Innovations, 8(5), 13203–13214.
17. Neela, S. (2022). Toward Intelligent Enterprise Integration: Cloud-Native Middleware Design Patterns and Adaptive Stream Orchestration Architectures for Autonomous Real-Time Decisioning. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 3(2), 154-164.
18. Tarigoppula, S. (2023). Cloud-native Oracle database modernization using intelligent migration frameworks and automated recovery architectures. International Journal of Research and Applied Innovations, 6(6), 10159–10171.
19. Vemireddy, S. (2022). Architecting personalized tax advisory experiences through event-driven customer data integration. International Journal of Research Publications in Engineering, Technology and Management, 5(6), 7923–7929.
20. Karrothu, A. (2025). Exploitability-aware vulnerability prioritization for automated security enforcement in cloud-native applications. International Journal of Research and Applied Innovations, 8(2), 11317–11331.
21. Abd-Rouf, M. S. K., Adigun, P. O., Alalade, E. O., Oyekanmi, T. T., Faniyi, A. J., Oladapo, B., Awopejo, T. E., Adegoke, O. S., Jamiu, A., Michael, O. B., Obisesan, A., Ajala, S., Adekanye, M. A., Yambali, P. M., & Abd-Rouf, A. B. (2024). From molecular profiling to predictive algorithms: A conceptual machine-learning framework for mechanism-informed therapy selection in multidrug-resistant cancer. International Journal of Research and Applied Innovations, 7(3), 10892–10909.
22. Ahuja, D. (2023). Multi-cloud management strategies: Tools, challenges, and implementation methods. Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol, 9(10), 493-506.
23. Basavala, S. R. (2024). Zero trust API security architecture for microservices-based enterprise applications. International Journal of Computer Technology and Electronics Communication, 7(4), 9269–9280.
24. Garg, D. (2025). Warehouse management system with IoT: A comprehensive guide. International Journal of Computer Engineering & Technology, 16, 2320–2332.
25. Gowda, M. K. S. (2026). Next-Gen risk frameworks ML integration for credit monitoring and governance. International Journal of Humanities and Information Technology, 8(1), 180–187. https://ijhit.info/index.php/ijhit/article/view/422
26. Valavala, S. K. (2024). From application logs to audit evidence in financial microservices. International Journal of Research and Applied Innovations, 7(4), 11246–11256.
27. Mudunuri, P. R. (2024). Designing high-availability automation architectures for mission-critical research systems. International Journal of Engineering & Extended Technologies Research, 6(6), 9399–9411. https://doi.org/10.15662/IJEETR.2024.0606038
28. Ramasamy, M. (2026). Microservices-Based Architectures for Enterprise Network Orchestration and Assurance. International Journal of Research and Applied Innovations, 9(2), 156-166.
29. Aragani, V. M., Maroju, P. K., & Mudunuri, L. N. R. (2024, December). Implementing Non-functional Production Regression Testing with Kubernetes. In International Conference on Information and Communication Technology for Competitive Strategies (pp. 231-244). Singapore: Springer Nature Singapore.
30. Kalakoti, M. K. R. (2023). AI-driven infrastructure orchestration for large-scale e-commerce platforms during global product launches. International Journal of Computer Technology and Electronics Communication, 6(4), 7388–7399.

31. Randhi, K. S. (2023). A cloud-native integration framework for enterprise architecture intelligence and application rationalization. International Journal of Science, Research and Technology (IJSRAT), 6(4), 10230–10240.
32. Karuturi, Y. (2025). Kubernetes-based containerization framework for SAP S/4HANA workloads in hybrid cloud environments. International Journal of Engineering & Extended Technologies Research, 7(6), 11382–11391.
33. Suddala, V. R. A. K. (2024). Machine learning for operational excellence: Real-world applications. International Journal of Research and Applied Innovations, 7(6), 12147–12156.
34. Gantikota, S. (2024). Shift-Left Security for Decentralized Engineering Organizations: Embedding SAST, DAST, and Penetration Testing Throughout the Software Development Lifecycle in University and Research Computing Environments. International Journal of Emerging Research in Engineering and Technology, 5(4), 175-179.
35. Shaik, N. (2024). Right-sizing at scale: A data-driven approach to Kubernetes cost optimization. International Journal of Research Publications in Engineering, Technology and Management, 7(1), 10080–10090.
36. Ambati, K. C. (2026). Unified supply chain intelligence data, AI, cloud, and operations synergy. International Journal of Humanities and Information Technology, 8(1), 173–179. https://ijhit.info/index.php/ijhit/article/view/424
37. Ponugoti, M. (2025). Cloud-Native Platform Engineering: Scalable Design Patterns for Global Enterprise Resilience. Journal of Computer Science and Technology Studies, 7(8), 48-59.
38. Bellundagi, M. (2025). Cloud-based smart retail system using AI-driven recommendations. The Eastasouth Journal of Information System and Computer Science, 3(1), 244–254. https://doi.org/10.58812/esiscs.v3i01.1298