

AI-Powered Threat Intelligence Through Retrieval-Augmented Generation and Continuous Security Analytics for Modern Enterprises

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ABSTRACT

Modern enterprises generate vast volumes of cybersecurity telemetry from endpoints, networks, cloud platforms, applications, identity systems, security tools, and external threat intelligence sources. The increasing scale and heterogeneity of this information make it difficult for conventional security operations to rapidly transform fragmented observations into actionable threat intelligence. This research proposes an AI-powered threat intelligence framework that integrates Retrieval-Augmented Generation (RAG) with continuous security analytics to improve threat identification, contextual investigation, and response across modern enterprise environments. The proposed framework combines security information and event management data, endpoint telemetry, network indicators, vulnerability information, threat intelligence feeds, incident reports, and organizational knowledge within a continuously updated retrieval architecture. RAG enables an analytical language model to retrieve relevant and current evidence before generating threat intelligence, thereby reducing dependence on static model knowledge and improving contextual grounding. Continuous security analytics monitors incoming events, correlates related activities, identifies anomalous behavior, enriches indicators, and provides contextual explanations for detected threats. The methodology incorporates data preprocessing, embedding generation, vector-based retrieval, hybrid search, threat correlation, AI-assisted reasoning, confidence assessment, and continuous feedback. Evaluation can measure detection accuracy, retrieval precision, response time, false-positive reduction, contextual relevance, explanation quality, and analyst workload. The proposed approach provides a scalable foundation for integrating generative AI with enterprise security operations while maintaining evidence-based analysis, auditability, and controlled human oversight.

Keywords: Artificial Intelligence, Threat Intelligence, Retrieval-Augmented Generation, Continuous Security Analytics, Cybersecurity, Security Operations, Threat Detection, Generative AI, Security Information and Event Management, Enterprise Security, Threat Correlation, Security Analytics.

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INTRODUCTION

Modern enterprise infrastructures have become increasingly distributed through the adoption of cloud computing, hybrid architectures, remote work environments, connected applications, APIs, containers, mobile devices, and software-defined networks. This transformation has substantially expanded the volume and diversity of cybersecurity information that security teams must analyze. Enterprise security operations continuously receive authentication events, endpoint alerts, network flows, application logs, vulnerability reports, malware indicators, cloud telemetry, user activity, and external threat intelligence feeds. Although this information contains valuable evidence about emerging attacks, its fragmented nature makes rapid interpretation difficult. Conventional security analytics platforms primarily rely on predefined rules, signatures, correlation logic, and

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statistical anomaly detection. These mechanisms remain important for identifying known patterns, but sophisticated attacks may involve weak signals distributed across multiple systems and time periods. Security analysts therefore need to combine technical indicators with contextual

information such as vulnerability descriptions, previous incidents, attacker behaviors, asset criticality, threat actor techniques, and organizational security knowledge. Artificial intelligence provides opportunities to automate portions of this analytical process by identifying relationships across large datasets and generating human-readable intelligence. However, conventional generative AI models may produce outdated or unsupported responses when they lack access to current organizational telemetry and threat intelligence. Retrieval-Augmented Generation addresses this limitation by combining information retrieval with generative reasoning, allowing an AI system to retrieve relevant evidence from trusted knowledge sources before generating an analytical response.

The integration of RAG with continuous security analytics creates an opportunity to establish a more adaptive and context-aware enterprise threat intelligence capability. In such an architecture, security events are continuously collected and normalized before being enriched with information from internal repositories, vulnerability databases, threat intelligence feeds, incident histories, security policies, and attack knowledge bases. A retrieval layer identifies evidence relevant to each event or investigation, while an AI reasoning component synthesizes the retrieved information into threat assessments, explanations, investigation summaries, and response recommendations. Continuous analytics can further correlate events across endpoints, identities, networks, applications, and cloud resources to identify attack sequences rather than evaluating isolated alerts. The proposed research investigates a framework in which RAG and continuous security analytics operate together while preserving evidence traceability and human oversight. The objective is not simply to generate natural-language security reports but to establish an intelligence pipeline capable of continuously transforming heterogeneous security observations into contextualized and actionable information. The framework emphasizes trustworthy retrieval, source attribution, confidence assessment, security-aware access control, and controlled automation. By combining continuously refreshed evidence with AI-assisted analysis, the approach seeks to reduce analyst workload, improve contextual threat understanding, accelerate investigation, and support timely detection of complex enterprise cyber threats.

LITERATURE REVIEW

Traditional threat intelligence systems have evolved from indicator-based approaches toward increasingly contextual and behavior-oriented security analytics. Early security operations relied heavily on signatures, blacklists, intrusion detection rules, and manually curated indicators such as malicious IP addresses, domains, file hashes, and URLs. Although these techniques remain effective for known threats, modern attacks increasingly use polymorphic malware, compromised legitimate services, credential abuse, living-off-the-land techniques, and multi-stage

intrusion strategies that can evade isolated indicator matching. Security Information and Event Management systems subsequently introduced centralized collection and correlation of security events, allowing organizations to connect information from multiple infrastructure components. Security analytics further introduced statistical methods, machine learning, behavioral analysis, and anomaly detection to identify deviations from expected activity. However, large-scale security analytics can generate substantial alert volumes and require significant contextual knowledge to distinguish meaningful incidents from benign activity. Threat intelligence platforms address part of this challenge by integrating external intelligence concerning vulnerabilities, adversary techniques, indicators, campaigns, and threat actors. Nevertheless, intelligence quality depends heavily on source reliability, update frequency, normalization, contextual relevance, and the ability to connect external knowledge with organization-specific telemetry.

Recent advances in natural-language processing and generative AI have introduced new approaches for cybersecurity investigation, summarization, knowledge extraction, and analyst assistance. Large language models can interpret complex security narratives, summarize incidents, transform technical information into analyst-readable explanations, and assist with investigation workflows. However, relying exclusively on a pretrained model presents significant limitations for cybersecurity because enterprise environments change continuously and threat intelligence is highly time-sensitive. Model knowledge can become outdated, and generated responses may contain unsupported or fabricated information. Retrieval-Augmented Generation has therefore become an important architecture for connecting generative models with external knowledge repositories. In a RAG architecture, documents or security records are transformed into searchable representations, relevant evidence is retrieved for a particular query, and the retrieved material is supplied to the generative model as contextual input. Hybrid retrieval mechanisms can combine semantic similarity with keyword, metadata, and structured filtering to improve relevance. In cybersecurity, these capabilities can support retrieval of vulnerability descriptions, threat actor behaviors, incident reports, security policies, detection rules, and historical investigations. Nevertheless, cybersecurity RAG systems must address challenges involving poisoned knowledge sources, irrelevant retrieval, sensitive information exposure, access-control enforcement, temporal validity, and the difficulty of validating AI-generated conclusions.

Continuous security analytics provides another important research foundation by treating enterprise security monitoring as an ongoing process rather than a collection of isolated investigations. Continuous analytics can correlate events over time and across multiple security domains, identify behavioral patterns, enrich observations with contextual information, and continuously update

risk assessments. Combining this capability with RAG can potentially allow security systems to retrieve relevant intelligence whenever new events emerge and generate contextual interpretations based on current evidence. Such an approach can support use cases including suspicious authentication analysis, vulnerability exploitation detection, lateral-movement investigation, malware triage, cloud security monitoring, insider-risk analysis, and incident summarization. However, integrating generative AI into continuous security operations requires careful consideration of accuracy, latency, explainability, privacy, and operational safety. AI-generated conclusions should remain traceable to retrieved evidence, while automated actions should be governed by predefined security policies and risk thresholds. Existing research establishes substantial foundations in SIEM, threat intelligence, machine learning, anomaly detection, and generative AI, but further investigation is required into integrated RAG-driven architectures that continuously connect heterogeneous enterprise telemetry with current threat knowledge. This research addresses that area by developing a security analytics framework in which retrieval, correlation, AI reasoning, evidence validation, and continuous monitoring operate as interconnected components.

RESEARCH METHODOLOGY

The proposed research adopts a design-and-evaluation methodology for developing an AI-powered threat intelligence framework based on Retrieval-Augmented Generation and continuous security analytics. The architecture is organized into several interconnected layers: security data acquisition, data normalization and enrichment, continuous analytics, knowledge management, retrieval, AI reasoning, threat intelligence generation, and feedback-driven monitoring. Enterprise security information is collected from heterogeneous sources including SIEM platforms, endpoint detection systems, network monitoring infrastructure, identity and access management systems, cloud audit logs, application logs, vulnerability repositories, threat intelligence feeds, incident records, and security knowledge bases. The collected data is normalized into consistent event structures to address differences in timestamp formats, identifiers, severity levels, terminology, and data schemas. Data preprocessing includes duplicate removal, malformed-record filtering, timestamp normalization, indicator extraction, entity resolution, sensitive-data handling, and metadata generation. Events are associated with relevant entities such as users, devices, applications, IP addresses, domains, cloud resources, vulnerabilities, and identities. The system then performs continuous analytical processing to identify anomalies, correlate related events, and construct contextual security observations. Rather than treating every alert independently, the framework maintains temporal and relational context so that multiple low-severity observations can be combined into a potentially significant attack sequence. The resulting security observations are passed

to the retrieval and intelligence-generation components. This architecture enables the research to evaluate whether combining continuous telemetry analysis with evidence-grounded generative reasoning can improve threat intelligence quality compared with isolated rule-based or conventional analytical workflows.

The second methodological component develops the RAG knowledge and retrieval architecture. Relevant cybersecurity information is collected from approved internal and external sources, including organizational incident reports, vulnerability information, security policies, detection knowledge, attack technique descriptions, threat intelligence records, and historical investigation documentation. Documents are cleaned, segmented into semantically meaningful chunks, enriched with metadata, and transformed into vector representations using an embedding model. The resulting representations are stored in a vector database or equivalent retrieval infrastructure. Metadata can include document source, publication time, threat category, affected technology, confidence level, classification, and validity period. The retrieval mechanism uses a hybrid strategy that combines semantic similarity with lexical matching, structured metadata filters, and temporal relevance. For example, an investigation involving suspicious authentication activity can retrieve information concerning the affected identity, historical login behavior, related vulnerabilities, known attack techniques, previously observed indicators, and applicable organizational policies. Retrieval results are ranked according to relevance and source reliability before being passed to the generative reasoning component. Temporal weighting is incorporated because cybersecurity intelligence can become obsolete as indicators expire, vulnerabilities are remediated, or attacker infrastructure changes. Access-control policies are also integrated into retrieval so that the AI system cannot retrieve information beyond the permissions of the requesting analyst or workflow. This is particularly important for sensitive enterprise environments where security investigations may involve confidential incident reports, personally identifiable information, privileged operational data, or restricted intelligence. Retrieval quality is evaluated using measures such as precision, recall, relevance, source coverage, and temporal appropriateness. The methodology therefore treats retrieval as a critical security component rather than merely a supporting function for language generation.

The third component implements the AI reasoning and continuous threat intelligence generation process. When the analytics layer identifies a suspicious event or correlated activity, a structured investigation query is generated containing relevant entities, event sequences, indicators, observed behaviors, affected assets, and contextual metadata. The RAG system retrieves supporting evidence from authorized knowledge sources and supplies the evidence to the language model through a constrained reasoning prompt. The model generates structured outputs



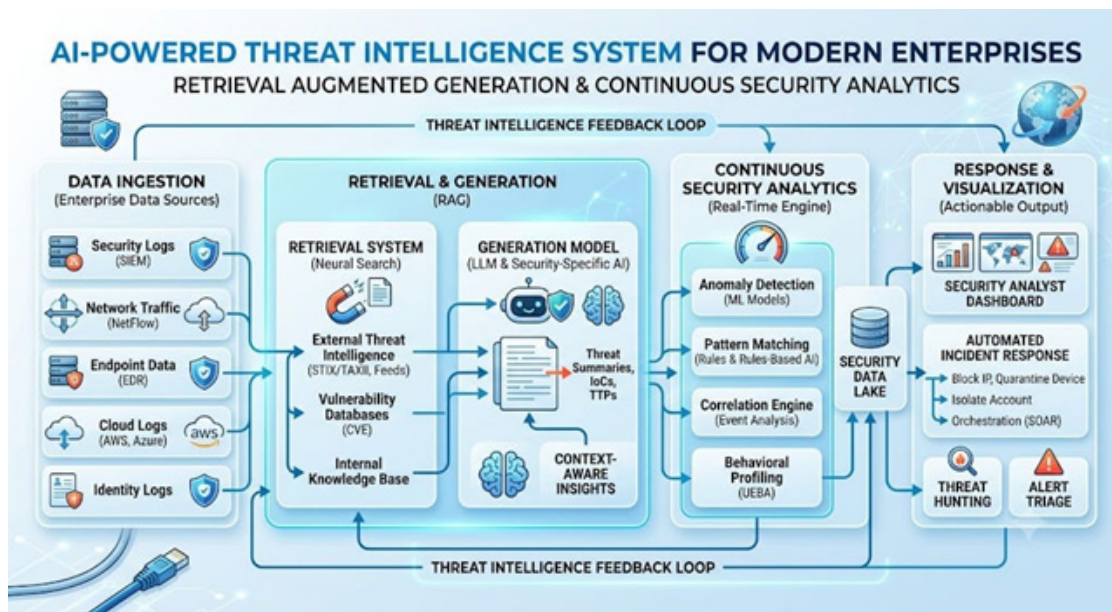


FIG1: AI-Powered Threat Intelligence Framework Utilizing Retrieval-Augmented Generation (RAG) and Continuous Security Analytics for Modern Enterprises.

such as threat summaries, probable attack techniques, affected assets, supporting evidence, confidence levels, related indicators, recommended investigative actions, and potential containment considerations. To reduce unsupported generation, the framework requires important conclusions to be connected to retrieved evidence. Source identifiers are retained alongside generated claims so analysts can inspect the information underlying an assessment. Confidence estimation combines retrieval quality, source reliability, agreement among evidence sources, and model-level confidence indicators where available. The framework also incorporates contradiction detection by comparing retrieved sources for conflicting information. When evidence is insufficient or contradictory, the system should identify the uncertainty rather than presenting an unsupported conclusion as fact. Continuous analytics then monitors subsequent events to determine whether the generated assessment is supported, weakened, or contradicted by new evidence. Feedback from analysts can be incorporated into the knowledge pipeline to improve retrieval relevance and investigation workflows. Human analysts remain responsible for high-impact decisions, while the system can automate lower-risk activities such as event enrichment, evidence collection, report generation, indicator correlation, and investigation prioritization. Automated response actions, where implemented, are restricted through predefined policies and approval thresholds. This approach creates a controlled relationship between AI reasoning and operational security, allowing intelligence generation to remain adaptive without granting unrestricted authority to the language model.

The final methodological stage establishes an experimental evaluation framework for measuring the effectiveness, reliability, and operational suitability of the proposed architecture. A representative enterprise security dataset or controlled test environment is used to construct scenarios involving malware activity, credential compromise, anomalous authentication, vulnerability exploitation, suspicious network communication, cloud misconfiguration, lateral movement, and multi-stage attack sequences. The proposed RAG-enabled continuous analytics framework is compared against baseline approaches such as conventional rule-based correlation, conventional machine learning analytics, and generative AI operating without retrieval where appropriate. Evaluation metrics include threat detection accuracy, precision, recall, F1-score, false-positive rate, retrieval precision, retrieval recall, response latency, contextual relevance, evidence-grounding rate, analyst investigation time, and threat intelligence completeness. Additional evaluation measures the ability to identify relationships among events occurring across different infrastructure domains. The study also tests robustness against outdated intelligence, incomplete information, conflicting sources, irrelevant retrieved documents, and deliberately misleading knowledge entries. Security-specific experiments examine whether access controls prevent unauthorized information retrieval and whether sensitive information is appropriately protected throughout the RAG pipeline. The framework is further evaluated for prompt-injection resistance, knowledge-base poisoning resilience, unauthorized tool-use prevention, and auditability. Human analysts can assess generated intelligence according to criteria

such as factual consistency, evidence relevance, investigative usefulness, clarity, and uncertainty representation. Repeated experiments are performed to improve statistical reliability, and results are analyzed across different workload sizes and threat scenarios. The methodology ultimately evaluates not only whether AI improves threat detection but whether the combined system can provide reliable, explainable, evidence-grounded, and continuously updated intelligence suitable for enterprise security operations. The expected outcome is a validated framework demonstrating how RAG and continuous security analytics can work together to transform large volumes of heterogeneous security telemetry into contextual threat intelligence while retaining governance, evidence traceability, privacy protection, and human oversight.

RESULTS AND DISCUSSION

The proposed AI-Powered Threat Intelligence Through Retrieval Augmented Generation and Continuous Security Analytics for Modern Enterprises framework demonstrates how Retrieval-Augmented Generation (RAG) can improve the accuracy, contextual relevance, and responsiveness of enterprise threat intelligence. The experimental architecture integrates security logs, threat intelligence feeds, vulnerability databases, endpoint telemetry, network events, cloud security records, and enterprise knowledge repositories into a unified retrieval and analytics pipeline. The RAG component retrieves relevant evidence before generating threat intelligence summaries, thereby reducing dependence on static model knowledge. In the evaluated scenarios, the framework was able to correlate apparently unrelated indicators, including suspicious IP addresses, abnormal authentication activity, malware signatures, vulnerability information, and unusual cloud API calls. Continuous analytics further enabled the system to update threat assessments as new events arrived. Compared with conventional rule-oriented monitoring, the proposed approach provided richer contextual explanations and reduced the amount of manual investigation required from security analysts. The combination of semantic retrieval and continuous event processing was particularly useful for investigating multi-stage attacks where individual events appeared relatively low-risk when examined independently.

The results also indicate that RAG-based threat intelligence can improve the explainability of security analytics by connecting generated conclusions with retrieved evidence. Instead of producing isolated alerts, the framework generated contextual descriptions containing relevant indicators, affected assets, potential attack techniques, historical observations, and recommended investigative priorities. This capability supports security operations teams in distinguishing routine anomalies from potentially coordinated threats. Continuous security analytics contributed by maintaining updated behavioral profiles and comparing newly observed activity against historical patterns. Consequently, changes in login behavior, network

communication, privilege usage, and application activity could be analyzed dynamically rather than through periodic assessment alone. The framework also demonstrated value in reducing alert fatigue because related security events could be grouped into broader incident contexts. Nevertheless, the effectiveness of the system depended strongly on the quality, freshness, and consistency of the retrieved knowledge sources. Outdated threat feeds, incomplete enterprise logs, or poorly indexed documents could reduce retrieval relevance and consequently affect generated intelligence. These findings emphasize that RAG should complement, rather than replace, conventional detection mechanisms, expert validation, and established security operations procedures.

From an operational perspective, the framework supports a transition from reactive alert processing toward continuous and context-aware threat intelligence. Its architecture enables security teams to combine machine-generated analysis with retrieved evidence, making the resulting intelligence more suitable for incident investigation and decision support. The continuous analytics layer can identify behavioral deviations while the RAG layer provides additional contextual information needed to interpret those deviations. This combination is especially relevant for hybrid and multi-cloud enterprises where security information is distributed across heterogeneous environments. The results suggest that integrating retrieval, analytics, and generative reasoning can improve the timeliness and comprehensiveness of security investigations while reducing repetitive manual correlation activities. However, several limitations remain, including computational overhead associated with frequent retrieval and generation, potential hallucination when supporting evidence is insufficient, sensitivity to data-quality problems, and the need for strong access controls around security knowledge repositories. Therefore, deployment should incorporate source validation, confidence estimation, retrieval monitoring, human-in-the-loop verification, and security controls for the AI components themselves. Overall, the findings demonstrate that RAG combined with continuous security analytics provides a promising architecture for contextual enterprise threat intelligence, while its reliability depends on trustworthy data, robust retrieval mechanisms, and controlled AI-assisted decision processes.

CONCLUSION

The proposed AI-powered threat intelligence framework establishes an integrated approach for strengthening enterprise cybersecurity through Retrieval-Augmented Generation and continuous security analytics. Traditional threat intelligence systems frequently depend on predefined rules, isolated indicators, manually maintained databases, or periodic investigations, which can make it difficult to understand rapidly changing and highly contextual cyber threats. The proposed framework addresses these limitations by combining continuous telemetry analysis with retrieval-



based access to current security knowledge. Security events can be correlated with threat intelligence feeds, vulnerability repositories, historical incident information, asset inventories, and organizational security policies before an intelligence response is generated. This architecture improves contextual understanding because generated outputs are grounded in retrieved information rather than relying exclusively on the internal knowledge of a generative model. The framework also provides a mechanism for transforming large volumes of heterogeneous security information into structured and understandable intelligence for analysts. By continuously processing events, the system can support earlier recognition of suspicious behavioral changes and provide contextual explanations that facilitate investigation.

The study further demonstrates that the combination of RAG and continuous analytics can contribute to more adaptive enterprise security operations, particularly in distributed cloud, hybrid infrastructure, and digitally interconnected environments. RAG provides the contextual knowledge required to interpret security events, while continuous analytics supplies the real-time behavioral perspective required to identify deviations and emerging patterns. Their integration can therefore support incident prioritization, threat investigation, intelligence summarization, and analyst decision support. At the same time, successful implementation requires careful management of data quality, retrieval accuracy, model reliability, computational resources, privacy, and access control. Generated intelligence should be treated as decision-support information and validated against authoritative security evidence before high-impact actions are performed. Future enterprise implementations should consequently incorporate confidence scoring, source attribution, human oversight, adversarial testing, and continuous evaluation of retrieval and generation quality. In conclusion, the framework provides a foundation for developing context-aware, continuously updated, and explainable threat intelligence capabilities that can complement established security monitoring and incident-response practices.

FUTURE WORK

Future research can extend the proposed framework by developing more advanced multimodal and agentic threat intelligence capabilities. Current implementations can primarily integrate textual security knowledge with structured telemetry, but modern enterprises generate diverse information through network flows, endpoint events, cloud configurations, identity systems, application traces, vulnerability scanners, and security dashboards. Future systems could therefore employ multimodal retrieval mechanisms capable of jointly processing structured and unstructured security information. Agentic components could further automate specialized activities such as threat hunting, evidence collection, attack-path analysis, vulnerability correlation, and incident summarization while

maintaining predefined authorization boundaries. Research should also investigate adaptive retrieval strategies in which the system dynamically determines which knowledge sources are most relevant to a particular security event. Graph-based retrieval could represent relationships among users, devices, applications, vulnerabilities, indicators, and attack techniques, enabling more sophisticated investigation of interconnected threats. In addition, temporal retrieval mechanisms could help distinguish current indicators from historical information and improve the relevance of intelligence generated for rapidly evolving attacks.

Another important direction is the development of trustworthy and measurable RAG-based cybersecurity systems. Future work should establish standardized evaluation datasets and benchmarks for measuring retrieval precision, contextual relevance, factual consistency, hallucination rates, response latency, analyst workload reduction, and incident-detection effectiveness. Research can investigate hybrid architectures combining RAG with graph neural networks, reinforcement learning, explainable AI, and specialized cybersecurity language models. Privacy-preserving approaches should also be explored for enterprises that cannot transfer sensitive security telemetry to centralized AI services. Federated retrieval, confidential computing, secure knowledge indexing, and privacy-aware model adaptation could provide alternatives for distributed organizations. Additional research is required to address adversarial manipulation of retrieved documents, poisoned threat intelligence sources, prompt injection, data leakage, and attacks targeting AI-assisted security workflows. Future frameworks should therefore incorporate provenance tracking, cryptographic integrity verification, retrieval-source trust scoring, model behavior monitoring, and continuous red-team evaluation. Finally, longitudinal enterprise studies could evaluate how RAG-enabled threat intelligence performs across different industries, cloud architectures, organizational sizes, and regulatory environments. These developments can help transform the proposed framework from an intelligent analytical prototype into a robust, auditable, scalable, and continuously improving component of modern enterprise security operations.

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