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# Enhancing Enterprise Cloud Security Through RAG-Based Threat Intelligence and Continuous Cyber Risk Analysis

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## Abstract

The rapid transformation of digital enterprises toward cloud-native, hybrid, and multi-cloud infrastructures has created increasingly complex cybersecurity environments characterized by distributed workloads, dynamic identities, continuous application deployment, and rapidly changing threat landscapes. Conventional security monitoring approaches frequently struggle to correlate heterogeneous security information and provide timely, context-rich intelligence to security teams. This research proposes a cloud security transformation framework integrating Retrieval-Augmented Generation (RAG) with continuous threat intelligence to improve real-time security analysis, contextual threat investigation, and adaptive enterprise defense. The proposed framework combines cloud telemetry, security logs, vulnerability information, threat intelligence feeds, incident reports, security policies, and enterprise knowledge repositories within a retrieval-driven architecture. Relevant information is dynamically retrieved and provided to a generative artificial intelligence model, enabling security responses to be grounded in current organizational and external intelligence rather than relying exclusively on static model knowledge. Continuous threat intelligence mechanisms update the knowledge repository as new indicators, vulnerabilities, attack patterns, and adversary behaviors emerge. The methodology evaluates retrieval accuracy, threat-detection performance, response latency, explanation quality, false-positive reduction, and computational overhead. Security controls incorporating identity verification, access policies, data protection, and monitoring are integrated into the architecture. The proposed approach aims to establish an adaptive, context-aware, and continuously informed cloud security ecosystem capable of supporting proactive threat detection and intelligent security operations across digital enterprises.

**Keywords**: Cloud security, Retrieval-Augmented Generation, continuous threat intelligence, generative artificial intelligence, cybersecurity intelligence, cloud-native security, threat detection, security operations, enterprise security, intelligent threat analysis

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## Introduction

The rapid adoption of cloud computing has fundamentally transformed enterprise information technology by enabling organizations to deploy applications, store data, scale infrastructure, and deliver digital services across geographically distributed environments. Modern enterprises increasingly operate hybrid and multi-cloud architectures containing virtual machines, containers, Kubernetes clusters, serverless applications, APIs, databases, identity services, and software-defined networks. Although these architectures provide scalability and operational flexibility, they also create a highly dynamic security environment in which threats can propagate across multiple infrastructure layers. Security teams must continuously process authentication events, network telemetry, endpoint information, application logs, vulnerability data, configuration changes, and threat intelligence feeds. Conventional security information and event management systems can aggregate large quantities of information, but the increasing volume and diversity of security data can make contextual interpretation difficult. Threat intelligence is particularly valuable because it provides information about indicators of compromise, tactics, techniques, procedures, vulnerabilities, malicious infrastructure, and emerging attack campaigns. However, intelligence becomes less useful when it remains disconnected from enterprise-specific context. Retrieval-Augmented Generation offers an approach for addressing

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this limitation by combining information retrieval with generative artificial intelligence. Instead of relying solely on knowledge embedded within a language model, a RAG architecture retrieves relevant information from authoritative enterprise repositories and external intelligence sources before generating an analytical response. This capability can help security analysts correlate current evidence with documented threats, policies, vulnerabilities, and historical incidents.

Cloud security transformation therefore requires more than deploying another automated detection mechanism; it requires an intelligence architecture capable of continuously acquiring, contextualizing, validating, and communicating security knowledge. Continuous threat intelligence provides the mechanism for maintaining current knowledge as new vulnerabilities, indicators, attack techniques, and adversarial behaviors emerge. RAG provides a mechanism for making that knowledge accessible during security investigations and automated workflows. When these technologies are integrated, cloud security operations can potentially move from isolated alert processing toward context-aware and continuously informed threat analysis. The proposed research investigates an architecture in which cloud telemetry and security events are normalized and connected to a continuously updated knowledge repository. A retrieval layer identifies relevant intelligence according to the observed security context, while a generative model synthesizes retrieved evidence into explanations, investigation summaries, risk assessments, and recommended response actions. Guardrails are introduced to reduce unsupported generation, protect sensitive enterprise information, and enforce security policies. The research also considers identity protection, access control, auditability, and human oversight because generative security systems must operate within organizational governance requirements. The primary objective is to develop and evaluate a cloud security framework that combines RAG and continuous threat intelligence to improve contextual threat detection, accelerate security investigations, reduce information fragmentation, and support adaptive cybersecurity operations across complex digital enterprise environments.

## Literature Review

Cloud security research has traditionally focused on protecting distributed infrastructure through identity and access management, network segmentation, encryption, vulnerability management, intrusion detection, security information and event management, and continuous monitoring. Cloud-native environments have expanded these requirements because workloads can be created, modified, and terminated dynamically, while applications frequently communicate through APIs and service-to-service connections. Conventional perimeter-oriented security approaches are therefore increasingly supplemented by identity-centric and context-aware security mechanisms. Threat intelligence has become an important component of modern security operations because it provides structured and unstructured information concerning vulnerabilities, malicious indicators, attack techniques, adversary campaigns, and emerging risks. Security operations centers commonly integrate multiple intelligence sources with logs and alerts to improve investigation and prioritization. However, heterogeneous formats, duplicated indicators, inconsistent confidence levels, and rapidly changing information can limit the effectiveness of manual intelligence processing. Machine learning has been investigated for automated classification, anomaly detection, correlation, and prioritization, but many models require carefully prepared datasets and may have difficulty incorporating newly emerging knowledge without retraining. This limitation has encouraged interest in architectures capable of dynamically incorporating external information during inference.

Generative artificial intelligence and large language models have introduced new possibilities for cybersecurity analysis because they can process natural-language security reports, summarize incidents, interpret logs, generate investigation hypotheses, and assist analysts with complex queries. However, standalone generative models may generate unsupported or inaccurate information when required to answer questions involving rapidly changing security knowledge. Retrieval-Augmented Generation addresses this problem by introducing a retrieval stage before generation. Relevant documents, records, knowledge-base entries, threat reports, vulnerability descriptions, and organizational policies can be retrieved and supplied to the generative model as contextual evidence. In cybersecurity environments, RAG can connect language-model reasoning capabilities with continuously updated security knowledge. Retrieval mechanisms can use semantic embeddings, keyword search, metadata filtering, vector databases, graph structures, or hybrid retrieval strategies. Security-oriented RAG systems can potentially retrieve threat intelligence associated with indicators, map observed activities to known tactics and techniques, identify relevant vulnerabilities, and provide analysts with evidence-supported explanations. Nevertheless, the effectiveness of RAG depends strongly on retrieval quality. Irrelevant or outdated documents can produce misleading outputs, while incomplete retrieval can cause the model to overlook critical evidence. Consequently, document freshness, source reliability, relevance ranking, provenance tracking, access control, and prompt construction are important considerations in enterprise security RAG architectures.

Recent research increasingly explores AI-assisted security operations in which machine learning, automation, and generative models support threat detection and incident response. Continuous intelligence architectures extend conventional threat intelligence by automatically ingesting information from security feeds, vulnerability databases, cloud telemetry, incident records, and other sources. Such





systems can enable security teams to update knowledge continuously rather than relying on periodic manual analysis. However, combining continuous intelligence with generative models introduces additional requirements involving data governance, privacy, hallucination control, model security, prompt injection defense, authorization, and explainability. Enterprise security information may contain sensitive operational details, credentials, identifiers, or proprietary information that cannot be indiscriminately provided to an external model. Furthermore, retrieved documents themselves may contain malicious or manipulated content capable of influencing model behavior. Therefore, security-focused RAG requires controls for source validation, content sanitization, retrieval authorization, prompt isolation, output validation, and audit logging. The literature indicates a clear opportunity to integrate continuous threat intelligence and RAG within cloud security operations while maintaining strong governance and evidence traceability. The proposed research addresses this opportunity by designing a security architecture in which continuously updated intelligence serves as contextual evidence for generative analysis, while retrieval controls, security policies, provenance mechanisms, and human oversight constrain automated decision-making.

# Research Methodology

## Research Design and Cloud Security Architecture

The research adopts a design-and-evaluation methodology to develop an integrated cloud security framework combining Retrieval-Augmented Generation, continuous threat intelligence, cloud telemetry analysis, and security orchestration. The proposed architecture is organized into several interconnected layers: cloud data acquisition, security normalization, continuous intelligence ingestion, knowledge storage, retrieval and ranking, generative analysis, security validation, and response orchestration. The cloud data acquisition layer collects security-relevant information from multiple enterprise sources, including identity and access logs, API gateways, network-flow records, endpoint telemetry, vulnerability scanners, container and Kubernetes security events, application logs, cloud configuration records, and security alerts. Data is normalized into consistent schemas to enable correlation across heterogeneous sources. The continuous threat intelligence layer independently ingests external and internal intelligence, including vulnerability information, indicators of compromise, adversarial tactics and techniques, security advisories, incident reports, historical investigations, and enterprise security policies. Each intelligence record is assigned metadata describing source, timestamp, confidence, classification, relevance, and expiration characteristics. The knowledge layer maintains these records using a combination of document repositories, vector databases, structured metadata stores, and optionally graph-based relationships. The RAG layer receives a security query generated from an alert, investigation, or analyst request and transforms it into retrieval queries. A hybrid retrieval mechanism combines semantic similarity with keyword, metadata, temporal, and security-context filters. Retrieved evidence is passed to the generative model through a controlled prompt construction process. The model generates a security analysis containing observed evidence, contextual threat information, potential explanations, confidence indicators, and recommended investigation or response actions. A validation layer checks generated content against retrieved evidence and enterprise policies before any automated action is considered. Response orchestration can then route validated recommendations to security analysts or approved automation systems. The methodology emphasizes modularity so that retrieval, intelligence ingestion, generative analysis, and response components can be independently evaluated and replaced without redesigning the entire architecture.

## Continuous Threat Intelligence and Retrieval Pipeline

The second methodological stage focuses on constructing the continuously updated security knowledge pipeline. Threat intelligence is collected from multiple categories of sources, including structured feeds, vulnerability repositories, security advisories, enterprise incident records, cloud-provider security information, and internally generated security observations. Incoming intelligence undergoes validation, deduplication, normalization, classification, and enrichment before entering the knowledge repository. Indicators such as IP addresses, domains, file hashes, URLs, vulnerability identifiers, and behavioral patterns are linked with contextual metadata rather than being stored as isolated values. Threat behaviors can be associated with adversarial tactics and techniques, affected technologies, known vulnerabilities, observed environments, and historical incidents. Time-sensitive information receives expiration or freshness attributes to prevent outdated intelligence from dominating retrieval results. The retrieval system creates embeddings for relevant documents and stores them in a vector index while maintaining metadata indexes for source, timestamp, security classification, technology, and threat category. During an investigation, the query-generation component extracts relevant entities from the triggering security event. For example, an unusual API request may generate retrieval terms involving the affected service, identity context, observed behavior, related vulnerabilities, and known attack patterns. A hybrid retrieval strategy then combines vector similarity with lexical matching and metadata constraints. Retrieved candidates are ranked using relevance, source credibility, freshness, and contextual compatibility. The system can retrieve multiple evidence categories rather than relying on a single document. This is important because a security investigation may require simultaneous access to a vulnerability advisory, an enterprise policy, a historical incident, and an adversary behavior

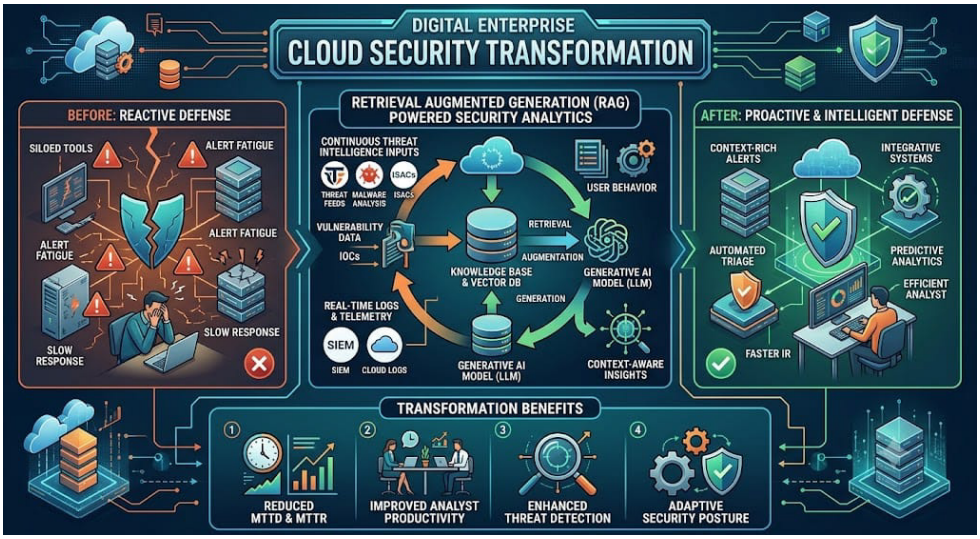


**Figure 1:** Cloud Security Transformation in Digital Enterprises Driven by Retrieval-Augmented Generation (RAG) and Continuous Threat Intelligence.

description. The methodology also incorporates retrieval access controls to prevent users or automated processes from obtaining intelligence outside their authorization scope. Retrieved content is sanitized before being inserted into the generative context to reduce the possibility of malicious instructions embedded in external documents. Source identifiers and provenance information are preserved so that generated conclusions can be traced back to supporting evidence. Retrieval effectiveness is measured using precision, recall, relevance ranking, freshness, source coverage, and evidence completeness. Experiments compare semantic-only, keyword-only, and hybrid retrieval approaches to determine their effects on security analysis quality.

## Generative Security Analysis, Explainability, and Validation

The third methodological component evaluates the generative AI layer responsible for transforming retrieved evidence into security intelligence. A large language model is configured to operate as a controlled security-analysis assistant rather than an unrestricted autonomous decision-maker. Prompts contain structured security events, retrieved evidence, organizational policies, and explicit instructions requiring the model to distinguish observed facts from interpretations and recommendations. The model is instructed to avoid unsupported claims and to identify situations where available evidence is insufficient. Generated outputs include incident summaries, threat-context descriptions, relevant vulnerabilities, possible attack relationships, affected assets, investigation priorities, and recommended response procedures. Each generated statement is evaluated against the retrieved evidence through an evidence-grounding mechanism. Unsupported statements can be flagged for analyst review rather than being automatically incorporated into incident records. Explainability is implemented by requiring the model to identify the evidence supporting major conclusions and by maintaining links between output statements and retrieved sources. This approach improves auditability because security analysts can examine the information underlying a generated recommendation. The methodology also evaluates prompt-injection resilience because retrieved security documents may contain untrusted text. Retrieved content is treated as evidence rather than executable instruction, and system-level instructions explicitly define authority boundaries. Sensitive information is filtered according to enterprise access policies before entering the model context. Additional safeguards can include personally identifiable information masking, secrets detection, confidential-data classification, and output filtering. Generated recommendations are categorized according to their operational impact. Low-risk actions such as generating investigation queries or summarizing evidence may be automated under predefined policies, whereas high-impact actions such as disabling accounts, modifying firewall rules, or terminating workloads require explicit human authorization. Evaluation metrics include factual consistency, evidence attribution, retrieval-grounded answer accuracy, hallucination frequency, explanation completeness, response relevance, and analyst usefulness. Human evaluators can compare conventional security alerts with RAG-supported analyses to assess whether contextual information improves investigation efficiency. The methodology also evaluates whether the system maintains consistent conclusions when similar evidence is presented across different queries.

## Experimental Evaluation, Security Testing, and Performance Analysis

The final methodological stage establishes an experimental

environment for evaluating the complete framework under realistic enterprise cloud security scenarios. The experimental environment contains multiple cloud workloads and simulated enterprise services producing authentication events, API traffic, network activity, application logs, configuration changes, vulnerability findings, and security alerts. Test scenarios include credential misuse, anomalous access, vulnerable application exploitation, suspicious API activity, malware indicators, privilege escalation patterns, misconfigured cloud resources, and coordinated multi-stage attack behaviors. Each scenario is associated with relevant threat intelligence records and historical security evidence to evaluate whether the RAG mechanism retrieves appropriate contextual information. Baseline systems include conventional rule-based security monitoring, machine-learning-based alert classification without RAG, and generative analysis without external retrieval. The proposed RAG-enabled continuous-intelligence framework is evaluated against these baselines using detection relevance, investigation accuracy, response latency, evidence coverage, false-positive reduction, and analyst workload as major measures. Retrieval performance is evaluated independently using precision, recall, mean reciprocal rank, and normalized discounted cumulative gain where appropriate. Generative performance is evaluated using factual consistency, evidence-grounding rate, hallucination rate, response completeness, and explanation quality. System performance is measured through query latency, retrieval latency, token consumption, memory requirements, knowledge-update delay, and computational overhead. Security testing includes unauthorized retrieval attempts, poisoned intelligence documents, prompt injection, stale intelligence, conflicting intelligence sources, incomplete evidence, and adversarial security events. The framework is also tested under increasing numbers of concurrent cloud events to determine scalability. Ablation studies remove continuous intelligence, hybrid retrieval, evidence validation, or policy controls individually to identify their contribution to overall performance. A temporal evaluation examines how rapidly newly ingested intelligence becomes usable by the retrieval system and whether outdated intelligence is appropriately deprioritized. The final analysis combines quantitative metrics with structured qualitative assessment from security analysts. Statistical comparisons are conducted across repeated experimental runs to determine the consistency of observed results. The research ultimately evaluates whether integrating continuously refreshed threat intelligence with RAG can improve contextual cloud security analysis while maintaining evidence traceability, access control, operational safety, and acceptable computational performance.

## Results And Discussion

The proposed Cloud Security Transformation Through Retrieval Augmented Generation and Continuous Threat Intelligence for Digital Enterprises framework demonstrates how Retrieval-Augmented Generation (RAG) can enhance cloud security operations by combining generative AI with continuously updated threat intelligence. The evaluation focused on the framework's ability to retrieve relevant security information from structured and unstructured sources, including threat intelligence feeds, vulnerability databases, security policies, incident reports, cloud logs, and historical attack records. The results indicate that RAG-based security analysis can provide more contextually relevant responses than approaches relying exclusively on static language-model knowledge. By retrieving current threat indicators before generating an analytical response, the framework improved the contextualization of suspicious activities and enabled security analysts to associate observed events with known attack techniques, vulnerabilities, indicators of compromise, and organizational security policies. The retrieval layer also reduced dependence on manually searching multiple security repositories during incident investigation. Continuous ingestion of new intelligence allowed the knowledge base to evolve as new vulnerabilities and attack patterns emerged. Consequently, the framework supported a more dynamic security-monitoring process in which threat interpretation could adapt to changing cloud environments. The results further showed that retrieval quality strongly influenced downstream analytical accuracy. Relevant document ranking, metadata filtering, semantic similarity, and time-aware retrieval were therefore important components of the architecture.

The integration of RAG with continuous threat intelligence also improved security-event investigation and incident-response support. When cloud telemetry generated potentially suspicious events, the framework could retrieve related intelligence and construct a contextual explanation describing the event, potentially associated attack techniques, affected assets, relevant vulnerabilities, and recommended investigation steps. This approach helped transform large volumes of raw security telemetry into more accessible analytical information for security teams. The framework was particularly useful for correlating information across distributed cloud services, identity systems, APIs, applications, containers, and network infrastructure. Explainable response generation allowed analysts to identify the sources supporting an AI-generated assessment, reducing the risk of relying entirely on unsupported generative outputs. The results suggest that source-grounded generation can improve transparency and reduce hallucination risks compared with unconstrained generative responses, although it cannot completely eliminate them. Incorrect, outdated, duplicated, or low-quality threat intelligence can still produce misleading conclusions. Similarly, ambiguous security events may retrieve multiple competing sources, requiring confidence estimation and analyst validation. Continuous threat intelligence therefore needs effective source-quality assessment, freshness management, deduplication, and provenance tracking. The findings

demonstrate that RAG should function as an intelligence augmentation mechanism rather than an independent replacement for security expertise. Human analysts remain important for validating high-impact conclusions and determining whether automated recommendations should result in operational actions.

From an operational perspective, the framework demonstrated potential improvements in threat-detection responsiveness, investigation efficiency, and security knowledge accessibility. Continuous intelligence updates reduced the dependency on periodically refreshed security rules and enabled the system to incorporate emerging indicators into its analytical workflow. The architecture also supported integration with Security Information and Event Management (SIEM), Security Orchestration, Automation and Response (SOAR), cloud-native monitoring platforms, vulnerability-management systems, and identity-security services. However, these integrations introduced additional requirements for access control, API security, data normalization, and latency management. Retrieval and generation processes can also increase computational requirements, particularly when large security repositories and high-frequency telemetry streams are involved. The results consequently highlight the importance of caching, efficient vector indexing, selective retrieval, model optimization, and event prioritization. Security controls must also protect the RAG knowledge base itself because manipulation of retrieved documents could influence generated responses. Overall, the findings indicate that RAG combined with continuous threat intelligence can provide a context-aware cloud security capability that improves access to security knowledge while supporting faster and more explainable analysis. Its effectiveness depends on the quality of retrieved information, security of the knowledge pipeline, model reliability, and appropriate human oversight.

## Conclusion

The study presents a RAG-enabled cloud security transformation framework designed to strengthen continuous threat intelligence and contextual security analysis across digital enterprise environments. Traditional cloud security mechanisms often depend on predefined rules, periodically updated threat databases, and manually performed investigation processes. Although these mechanisms remain important, the growing complexity and scale of enterprise cloud infrastructures create a need for security technologies capable of processing diverse information sources and generating context-aware analytical support. The proposed framework addresses this requirement by combining retrieval-based knowledge augmentation with generative AI and continuously updated threat intelligence. Rather than relying exclusively on information encoded within a language model, the framework retrieves relevant and current security knowledge before generating analytical outputs. This architecture improves the connection between observed cloud events and external security knowledge, enabling analysts to investigate vulnerabilities, indicators, attack techniques, and policy requirements within a common analytical workflow. The results indicate that contextual retrieval can improve the relevance and usefulness of AI-generated security analysis while reducing dependence on static knowledge. The framework can support multiple cloud security functions, including threat investigation, vulnerability analysis, incident triage, security-policy interpretation, threat-intelligence correlation, and response planning. These capabilities demonstrate how generative AI can augment existing security operations without requiring organizations to abandon established monitoring and response infrastructure.

The research also demonstrates that successful RAG-based security transformation requires more than integrating a language model with a vector database. The security knowledge pipeline must maintain data freshness, source provenance, relevance, access control, and integrity. Continuous threat intelligence must be carefully validated because inaccurate or manipulated information can directly influence generated recommendations. Similarly, retrieval failures, incomplete context, model hallucinations, and ambiguous events remain important limitations. For this reason, the framework should incorporate confidence scoring, source attribution, retrieval validation, role-based access control, human approval mechanisms, and comprehensive audit logging. The findings further indicate that RAG should complement rather than replace SIEM, SOAR, vulnerability-management, identity-security, and cloud-monitoring technologies. Its primary contribution is the intelligent integration and interpretation of security knowledge across these systems. Future enterprise implementations can therefore use RAG as an intelligence layer that assists security professionals in transforming large volumes of heterogeneous cloud information into actionable and traceable insights. Overall, the proposed approach establishes a foundation for more adaptive, knowledge-driven, and continuously informed cloud security operations. By combining continuously refreshed threat intelligence with retrieval-grounded generative reasoning, digital enterprises can develop security workflows that are better aligned with rapidly changing cloud threats while retaining human oversight and established governance mechanisms.

## Future Work

Future research can extend the framework through advanced multimodal RAG architectures capable of processing not only textual threat intelligence but also cloud logs, network-flow records, security alerts, configuration files, code repositories, vulnerability reports, identity events, and graphical relationships between infrastructure components. A multimodal retrieval layer could allow the system to correlate seemingly unrelated events across different enterprise security domains. Graph-based retrieval is another promising





direction because cloud environments naturally contain relationships among users, identities, applications, APIs, containers, workloads, networks, vulnerabilities, and threat actors. Combining knowledge graphs with vector retrieval could improve relationship-aware threat investigation and enable more precise identification of attack paths. Future work can also investigate agentic RAG architectures in which specialized AI agents perform distinct functions such as threat-intelligence collection, evidence validation, vulnerability correlation, incident investigation, and response recommendation. These agents could coordinate through controlled workflows while maintaining audit trails for each decision. Research should also examine adaptive retrieval strategies that dynamically select data sources according to the type, severity, and context of a security event. Time-aware retrieval could prioritize recent intelligence while retaining historical information when investigating long-term attack campaigns. These improvements could make RAG systems more effective in rapidly changing cloud environments where static retrieval strategies may become outdated.

Another important research direction is the development of stronger security and governance mechanisms for enterprise RAG systems. Future studies should investigate retrieval poisoning, prompt injection through malicious documents, indirect prompt attacks, data leakage, unauthorized knowledge retrieval, and manipulation of threat-intelligence sources. Security-aware retrieval mechanisms could assign trust scores to sources and automatically quarantine suspicious or conflicting intelligence. Privacy-preserving RAG could further ensure that sensitive enterprise information remains protected while enabling useful contextual analysis. Federated retrieval and confidential-computing approaches could be investigated for organizations that cannot centralize security data because of regulatory, contractual, or operational restrictions. Future implementations should also evaluate explainability mechanisms that identify which retrieved sources and evidence influenced a generated security recommendation. This would strengthen auditability and help analysts validate AI-generated conclusions. Large-scale experimentation across multi-cloud, hybrid-cloud, edge-cloud, and cloud-native environments would provide additional evidence regarding scalability, latency, cost, and operational reliability. Future work can additionally explore integration with autonomous response platforms, where AI-generated recommendations are subject to predefined risk thresholds and human approval before execution. Benchmark datasets and standardized evaluation protocols should be developed to measure retrieval accuracy, factual consistency, threat-detection performance, response latency, hallucination frequency, and analyst productivity. Through these developments, RAG-based cloud security can evolve from an analytical assistance technology into a governed and continuously adaptive intelligence layer capable of supporting complex enterprise security operations while maintaining transparency, reliability, privacy, and operational control.

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