International Journal of Technology, Management and Humanities Volume 12, Issue 3, 2026

Cross-Domain Threat Investigation for Enterprise Cloud Security Using Distributed AI Learning and Event Correlation

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Abstract

Enterprise cloud environments increasingly span public, private, hybrid, and multi-cloud infrastructures, creating complex security challenges that require coordinated investigation across multiple administrative and technological domains. Conventional security monitoring systems often analyze alerts independently, limiting their ability to identify sophisticated attacks that generate interconnected events across identities, networks, applications, containers, and data services. This research proposes an intelligent cross-domain threat investigation framework that integrates distributed artificial intelligence learning with event correlation to improve enterprise cloud security. The framework collects security events from heterogeneous cloud platforms, normalizes their representations, and correlates related activities using temporal relationships, entity associations, behavioral patterns, and attack sequences. Distributed AI learning enables participating domains to collaboratively improve threat detection while minimizing the need to exchange sensitive raw telemetry. Machine learning models identify anomalous behavior, prioritize suspicious event clusters, and support the reconstruction of potential attack paths. Graph-based correlation and contextual risk scoring connect isolated alerts into meaningful investigative narratives. The proposed architecture incorporates secure intelligence exchange, explainable predictions, privacy safeguards, and analyst-guided incident validation. Its evaluation methodology considers detection accuracy, correlation precision, investigation time, false-positive rates, processing latency, communication overhead, and cross-domain generalization. By combining distributed learning with contextual event analysis, the framework aims to improve visibility into coordinated cyberattacks, reduce fragmented investigations, and support timely, evidence-based incident response across enterprise cloud environments.

Keywords: Cross-domain threat investigation, Enterprise cloud security, Distributed AI learning, Security event correlation, Federated learning, Attack graph analysis, Threat intelligence, Anomaly detection

International Journal of Technology, Management and Humanities (2026)

Introduction

Enterprise cloud computing has transformed organizational information technology by enabling scalable infrastructure, distributed applications, flexible data storage, and integrated digital services. Organizations increasingly operate across public cloud providers, private data centers, hybrid infrastructures, containerized workloads, and software-as-a-service platforms. Although these environments improve operational flexibility, they also expand the cybersecurity attack surface and complicate the investigation of coordinated security incidents. A malicious campaign may begin with a compromised employee account, continue through unauthorized API access, exploit a vulnerable application, and eventually reach sensitive databases or cloud management services. Each activity may generate separate alerts within identity management systems, network monitoring tools, endpoint protection platforms, cloud audit services, and application security solutions.

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How to cite this article: Bhat, C.R. (2026). Cross-Domain Threat Investigation for Enterprise Cloud Security Using Distributed AI Learning and Event Correlation. *International Journal of Technology, Management and Humanities,* 12(3), 93-100.

Source of support: Nil

Conflict of interest: None

When these alerts are investigated independently, security analysts may struggle to recognize their relationships, determine the attack sequence, and identify the overall scope of a compromise. Differences in event formats, timestamp conventions, identity representations, logging policies, and access permissions further restrict cross-domain visibility.

Conventional security information and event management systems provide centralized aggregation and rule-based correlation, but complex attacks may evade predefined rules through distributed execution, low-frequency actions, legitimate credential abuse, and activity spread across multiple cloud environments. Furthermore, transferring all security telemetry into a centralized repository can introduce privacy concerns, regulatory constraints, network overhead, and operational dependencies. Consequently, enterprise cybersecurity requires investigation mechanisms that connect related events across administrative boundaries, recognize emerging attack patterns, and preserve the confidentiality of sensitive organizational information.

Distributed artificial intelligence learning and event correlation offer complementary capabilities for addressing these challenges. Distributed learning enables multiple cloud domains to improve shared threat-detection models while retaining their original datasets within local environments. Federated learning, for example, allows participating organizations or infrastructure domains to train local models and exchange model updates through a coordinated aggregation process, subject to suitable privacy and security controls. Event correlation complements this capability by identifying relationships among security observations using temporal proximity, shared identities, network connections, resource associations, behavioral similarities, and causal dependencies. Graph-based representations can connect users, devices, applications, containers, workloads, and data assets to reconstruct potential attack paths and support investigation prioritization. The integration of these techniques can help distinguish isolated anomalies from coordinated campaigns and provide analysts with a more complete view of suspicious activity. Nevertheless, practical implementation requires addressing heterogeneous telemetry, concept drift, unbalanced training data, malicious model updates, uncertain event relationships, communication latency, and explainability requirements. Privacy-preserving learning alone does not guarantee confidentiality, and event correlation alone does not establish that related events share a malicious cause. This research therefore proposes a cross-domain threat investigation framework that combines distributed AI learning, normalized security telemetry, graph-based event correlation, contextual risk scoring, and analyst-guided validation. Its principal objective is to improve the identification, reconstruction, and prioritization of coordinated cyberattacks across enterprise cloud environments while maintaining operational scalability, data protection, and investigative transparency.

Literature Review

Traditional enterprise security investigation has relied on security information and event management systems, intrusion detection platforms, centralized log analytics, and predefined correlation rules. These technologies aggregate records from network devices, identity services, operating systems, applications, and cloud control planes to support incident detection and investigation. Rule-based correlation can identify recognizable patterns, such as repeated authentication failures followed by a successful login or suspicious outbound communication following malware execution. However, predefined rules often depend on known indicators, fixed thresholds, and manually maintained relationships. Sophisticated attackers can avoid detection by distributing activities across different systems, using legitimate credentials, changing infrastructure, and introducing delays between attack stages. Machine learning has improved detection by learning behavioral patterns from historical telemetry and identifying anomalies that depart from established baselines. Supervised models can classify known attack behaviors, while unsupervised and semi-supervised approaches can discover suspicious patterns when labeled incidents are limited. Nevertheless, isolated classification models may generate large numbers of disconnected alerts without explaining how individual observations contribute to a broader attack. Performance can also deteriorate when models trained on one cloud environment encounter different traffic characteristics, identity policies, application architectures, or attack distributions. These limitations demonstrate the need to integrate event-level detection with cross-domain correlation and investigation-oriented context.

Distributed AI learning has attracted attention as organizations seek collaborative threat detection without unrestricted centralization of sensitive security data. Federated learning allows participating domains to train local models and contribute updates to a shared model, potentially improving generalization across different infrastructures. Other distributed approaches include decentralized learning, collaborative anomaly detection, and privacy-preserving model aggregation. These techniques can support the identification of common threat patterns while reducing the need to transfer raw telemetry between organizations. However, differences in local data distributions can produce inconsistent model performance, particularly when one domain observes predominantly authentication attacks while another encounters network exploitation or malware activity. Communication costs, participant availability, model convergence, and update integrity also influence practical effectiveness. Privacy risks remain because model updates may reveal information about local training records, making secure aggregation, access controls, and, where justified, differential privacy important design considerations. Malicious participants may submit manipulated updates or poison shared models, requiring contribution validation, anomaly monitoring, and robust aggregation mechanisms. Distributed learning therefore offers an important foundation for collaborative security analytics, but its effectiveness depends on careful treatment of data heterogeneity, privacy, trust, and operational constraints. A complete investigation framework must also translate learned patterns into



actionable evidence that security analysts can verify and interpret.

Event correlation research has explored temporal analysis, entity resolution, statistical association, graph analytics, attack-chain reconstruction, and causal reasoning to connect security observations. Graph-based methods represent entities as nodes and relationships as edges, allowing investigators to examine connections among users, IP addresses, cloud resources, applications, and suspicious activities. Temporal correlation can reveal sequences such as credential compromise, privilege escalation, lateral movement, and unauthorized data access. Threat intelligence can enrich these relationships with indicators of compromise and previously observed attack patterns. Structured representations such as STIX and exchange mechanisms such as TAXII can support interoperable threat intelligence workflows. Despite these advances, cross-domain investigations remain difficult when event schemas differ, clocks are inconsistent, entity identifiers are incomplete, and individual observations provide ambiguous evidence. Excessively permissive correlation may combine unrelated activities, while restrictive thresholds may fragment a genuine attack sequence. Research must therefore balance correlation precision, investigative coverage, processing speed, and explainability. An additional challenge is integrating the results of distributed model learning with event graphs in a way that preserves local data ownership and clearly distinguishes observed facts from inferred relationships. The research gap addressed by this study is the design and evaluation of a unified architecture that combines privacy-aware distributed learning, cross-domain event correlation, attack-path reconstruction, and evidence-based investigation prioritization. The proposed framework aims to improve coordinated threat identification without assuming that every statistical association represents a confirmed attack.

Research Methodology

Research Design and Cross-Domain Security Architecture. The research adopts a quantitative, experimental design to develop and evaluate a distributed AI-based framework for investigating cyber threats across enterprise cloud environments. The proposed architecture consists of six integrated components: multi-domain telemetry collection, event normalization, local AI learning, distributed model coordination, graph-based event correlation, and investigation and response management. The telemetry collection component obtains security records from public cloud control planes, private infrastructure, virtual machines, container orchestration platforms, identity and access management systems, API gateways, endpoint detection tools, firewalls, and enterprise applications. Each participating domain processes its records locally and extracts relevant features before sharing approved information with other domains or a coordinating service. The event normalization component converts heterogeneous records into a common representation containing event timestamps, source and destination entities, event categories, resource identifiers, authentication outcomes, network attributes, and available threat indicators. Timestamp normalization, duplicate removal, schema validation, and entity resolution are applied to improve consistency across sources. Where identifiers differ between domains, carefully controlled mapping procedures establish relationships without exposing unnecessary personal or organizational information. The architecture maintains distinct records for observed events, model predictions, inferred relationships, and analyst-confirmed findings. This separation prevents automatically generated correlations from being treated as established facts. A streaming architecture can use Apache Kafka or an equivalent message-processing platform to transport events, while graph storage and distributed processing components maintain relationships among entities and security observations. Authentication, encryption, role-based access control, audit logging, and retention policies protect the investigation process. The design supports heterogeneous cloud environments and intermittent domain connectivity, allowing local detection to continue when collaboration services are temporarily unavailable. Its effectiveness will be evaluated through detection quality, investigation completeness, response latency, resource consumption, and privacy-related communication requirements.

Distributed AI Learning and Local Threat Detection. The distributed learning component enables participating cloud domains to develop shared threat-detection capabilities while retaining raw security telemetry within their respective administrative boundaries. Each domain trains a local machine learning model using authorized historical events, validated incident records, and relevant behavioral features. Depending on the available data, candidate algorithms may include random forests, gradient-boosting models, autoencoders, or neural networks designed for sequential security observations. The model inputs may include authentication frequency, failed-login ratios, unusual access times, connection volumes, resource access sequences, API request patterns, privilege changes, and deviations from established workload behavior. Local models generate anomaly scores, event classifications, and contextual feature representations for downstream correlation. In a federated learning configuration, participating domains exchange model updates with a coordinator that performs aggregation using an algorithm such as Federated Averaging. Updated parameters are distributed back to participants for subsequent training rounds. Because enterprise domains frequently exhibit non-identically distributed data, the methodology will assess model performance across different attack types, traffic characteristics, and local class distributions. Where necessary, domain-specific calibration or personalization will be evaluated alongside a shared global model. Secure aggregation, authenticated

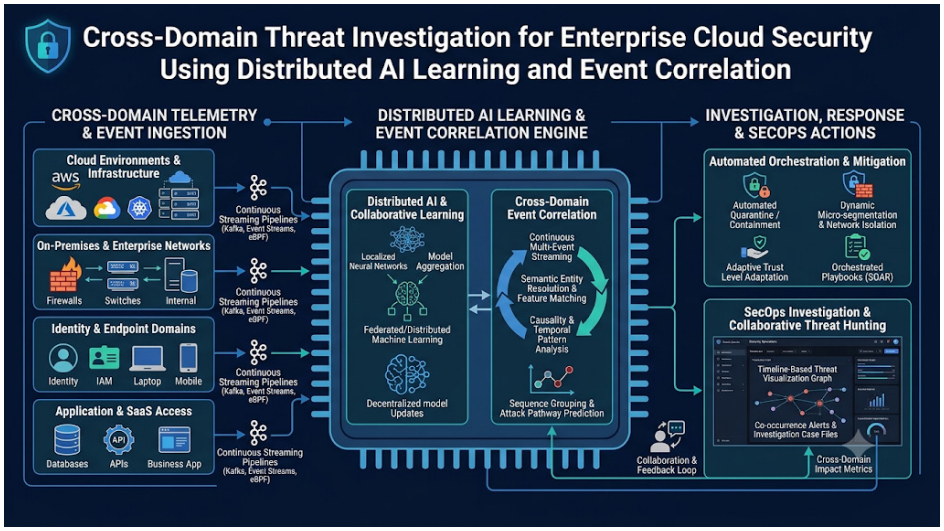


Figure 1: Comprehensive framework for Cross-Domain Threat Investigation in Enterprise Cloud Security utilizing Distributed AI Learning and Event Correlation.

participants, update validation, and anomaly checks will reduce exposure to malicious or corrupted contributions. Differential privacy may be applied when its privacy benefits justify the associated impact on model utility. Importantly, federated learning will not be assumed to guarantee privacy automatically; privacy leakage, communication overhead, convergence, and detection quality must be assessed experimentally. A conventional centralized model, where appropriate and ethically permissible, and independent local models will provide comparison baselines. The investigation will determine whether collaborative learning improves cross-domain threat recognition while maintaining acceptable computational cost, privacy safeguards, and local operational autonomy.

Event Correlation, Attack Reconstruction, and Investigation Prioritization. The event correlation component transforms individual security observations into connected investigative evidence. A temporal event processor first identifies candidate relationships using configurable time windows, entity identifiers, event types, and relevant behavioral attributes. A graph-based representation then models users, devices, IP addresses, cloud resources, applications, containers, and data repositories as nodes, with authentication, communication, resource access, privilege changes, and other observed interactions represented as edges. Event relationships receive attributes describing their source, timestamp, confidence, and supporting evidence. Correlation rules and similarity measures identify sequences that may indicate credential compromise, privilege escalation, lateral movement, command-and-control communication, or unauthorized data access. AI-generated anomaly scores from participating domains enrich these relationships, while distributed threat intelligence provides additional context where validated indicators are available. A contextual risk score can combine event severity, model confidence, relationship strength, temporal consistency, asset criticality, and intelligence reliability. The scoring process will use normalized features and validation-based weights rather than arbitrary assumptions about the importance of individual signals. Candidate attack paths will be reconstructed by examining connected event sequences and identifying plausible progression between affected entities. However, graph connectivity and temporal proximity alone cannot prove causation. Therefore, the system will distinguish direct observations, model-derived predictions, and inferred attack relationships, allowing analysts to review the evidence behind each investigative conclusion. Explainability methods, including feature attribution and concise graph-path summaries, will help investigators understand why an event cluster was prioritized. The framework will also support suppression of duplicate alerts, grouping of related incidents, and ranking by potential impact. Automated containment will remain subject to predefined authorization rules, with human approval required for sensitive actions such as disabling privileged accounts or isolating critical business systems. This approach aims to reduce fragmented investigations while preserving evidence quality, traceability, and analyst control.

Experimental Evaluation, Validation, and Performance Measurement. The framework will be evaluated using publicly available cybersecurity datasets, such as CICIDS2017, CSE-CIC-IDS2018, and UNSW-NB15, supplemented where feasible by authorized cloud audit logs, container security events, identity records, and controlled attack simulations. Since these datasets differ in their schemas and attack coverage, each dataset will be documented and mapped carefully to the common event representation. Synthetic cross-domain scenarios may connect compatible event types to simulate multi-stage incidents, but synthetic relationships will be clearly distinguished from naturally

observed attack sequences. Data leakage will be controlled through appropriate time-based or group-based training and testing splits, and all preprocessing, resampling, and model selection decisions will be restricted to the relevant training and validation partitions. The proposed framework will be compared against rule-based correlation, independent local machine learning models, centralized learning where appropriate, and graph correlation without distributed AI. Evaluation metrics will include precision, recall, macro-F1-score, false-positive rate, attack-path reconstruction accuracy, event-correlation precision and recall, investigation time, and detection latency. Operational measurements will include throughput, CPU and memory consumption, model convergence time, communication volume, and the overhead of privacy-preserving mechanisms. Ablation experiments will disable distributed learning, graph correlation, or threat intelligence enrichment individually to estimate each component's contribution. Additional tests will examine missing events, delayed messages, inconsistent timestamps, domain-specific data distributions, unavailable participants, and potentially poisoned model updates. Repeated trials and confidence intervals will quantify uncertainty, while statistical tests will be selected according to the data and assumptions. Where possible, analyst-centered evaluations will examine whether evidence summaries improve investigation accuracy and reduce time spent reviewing unrelated alerts. No numerical improvements will be claimed before experiments are conducted. The final analysis will report measured results, reproducibility details, limitations, and trade-offs, determining whether distributed AI learning and event correlation provide meaningful benefits for secure, scalable, and privacy-aware cross-domain threat investigation.

Results And Discussion

The proposed framework for cross-domain threat investigation integrates distributed artificial intelligence learning with event correlation to improve the identification, analysis, and investigation of cybersecurity incidents across enterprise cloud environments. The framework combines security information from multiple domains, including network infrastructure, identity and access management, cloud workloads, application services, endpoint protection, and API gateways. By correlating events generated across these domains, the system aims to identify relationships that may remain undetected when security alerts are investigated independently. For example, repeated authentication failures followed by an unusual successful login, unexpected privilege escalation, suspicious API activity, and abnormal outbound data transfers may indicate a coordinated attack involving multiple enterprise services. Distributed AI learning enables participating domains to contribute to collective threat detection without necessarily centralizing all raw security data. The expected benefits include improved contextual awareness, reduced investigation fragmentation, and more effective identification of complex attack sequences. Event correlation can employ temporal relationships, shared identifiers, behavioral similarities, and graph-based representations to connect apparently unrelated security events. However, the effectiveness of the proposed framework must be established through controlled experiments using representative enterprise security datasets and realistic cloud workloads. Evaluation should measure detection precision, recall, F1-score, false-positive rate, investigation time, and computational overhead. Comparative testing against rule-based monitoring, centralized machine learning, and independent domain-specific detection can determine whether distributed learning and cross-domain correlation provide measurable improvements in security investigation.

The distributed AI learning component supports collaborative model development across organizational units, cloud regions, and infrastructure providers. Instead of transferring every security log to a centralized repository, participating domains can train local models using their own telemetry and contribute model updates through an authenticated aggregation mechanism. This design can reduce unnecessary exposure of sensitive operational information while allowing the overall detection capability to benefit from diverse attack observations. Federated learning is a potential implementation approach, although its effectiveness depends on communication reliability, data quality, model compatibility, and the distribution of attack samples across participating domains. Cross-domain event correlation complements distributed learning by linking alerts according to timestamps, identity attributes, network relationships, resource identifiers, and observed attack behaviors. Graph-based correlation can represent relationships among users, devices, workloads, services, and suspicious indicators, enabling investigators to reconstruct potential attack paths and distinguish isolated anomalies from coordinated incidents. Nevertheless, differences in log formats, clock synchronization, identifier conventions, and security policies can complicate correlation. A practical implementation should therefore include normalized event schemas, timestamp alignment, identity resolution, confidence scoring, and mechanisms for handling missing or contradictory evidence. Distributed learning also requires protection against malicious model updates, data poisoning, and unauthorized participation. Secure aggregation, participant authentication, model validation, and privacy-preserving techniques can help address these risks. The resulting architecture is expected to improve collaborative analysis while maintaining appropriate boundaries between participating domains.

The discussion further emphasizes the importance of operational efficiency, interpretability, and reliable incident prioritization. Enterprise security teams frequently face large volumes of alerts, many of which are repetitive, weakly contextualized, or unrelated to significant incidents. Cross-domain correlation can consolidate related events into incident-level investigations, allowing analysts to

examine a connected sequence of suspicious activities rather than treating every alert as an independent problem. Distributed AI models can assign risk scores based on behavioral deviations, historical attack patterns, asset criticality, and corroborating evidence from other domains. Explainable investigation outputs can identify which events and relationships contributed to an incident assessment, improving analyst confidence and supporting audit requirements. However, excessive correlation may incorrectly combine unrelated events, while incomplete telemetry can prevent the reconstruction of genuine attack sequences. Accordingly, evaluation should examine correlation accuracy, alert reduction, incident reconstruction completeness, investigation duration, and analyst verification effort. Stress testing should include simultaneous attacks, delayed events, missing records, adversarial behavior, and intermittent communication between cloud domains. Results should be reported using measured values rather than assumed improvements, with confidence intervals and consistent baseline comparisons where appropriate. Overall, the integrated framework provides a promising approach to collaborative enterprise cloud security, but its practical effectiveness depends on rigorous validation, reliable data integration, and safeguards against erroneous or manipulated intelligence.

Conclusion

Cross-domain threat investigation is increasingly important for enterprise cloud security because modern organizations operate interconnected applications, distributed workloads, hybrid infrastructure, and multiple identity and access management systems. Security incidents frequently span these environments, making isolated monitoring and domain-specific analysis insufficient for understanding complex attack behavior. This research presents a framework that combines distributed AI learning and event correlation to strengthen threat detection, incident investigation, and coordinated security analysis across enterprise cloud domains. The framework integrates telemetry from networks, applications, endpoints, cloud platforms, authentication services, and APIs to identify relationships among suspicious activities. Distributed learning enables participating domains to contribute to collaborative threat detection while limiting the need to exchange raw operational records. Event correlation provides contextual relationships that support incident reconstruction, attack-path identification, and risk prioritization. Together, these capabilities can help security analysts move beyond isolated alerts toward a more comprehensive understanding of potential security incidents. The approach is relevant to multi-cloud and hybrid cloud organizations in which infrastructure ownership, data sensitivity, administrative responsibilities, and monitoring capabilities differ across environments. By combining local analytical capabilities with cross-domain intelligence, the proposed architecture establishes a foundation for coordinated security investigation while preserving appropriate domain boundaries. Its principal contribution is the integration of collaborative AI learning and contextual event correlation into a unified investigation process intended to improve visibility across distributed enterprise systems.

Successful implementation requires more than the integration of machine learning models and event processing components. The framework must address data interoperability, model reliability, communication overhead, privacy protection, access control, and the operational demands of real-time security monitoring. Event correlation should preserve temporal accuracy and distinguish strong relationships from coincidental similarities, while distributed learning must account for differences in local datasets and the possibility of compromised participants. Security teams should also be able to understand why an incident was prioritized, which evidence supports the classification, and where uncertainty remains. Consequently, practical deployments should incorporate confidence-based correlation, secure model aggregation, authenticated intelligence exchange, explainable risk assessments, and auditable investigation records. Performance should be validated against established security monitoring approaches using reproducible experiments and realistic enterprise workloads. Important metrics include precision, recall, false-positive rate, detection latency, investigation time, communication cost, and the accuracy of reconstructed attack sequences. The framework should not be considered empirically superior until these measurements demonstrate consistent improvements under comparable testing conditions. Future implementation should also evaluate the impact of missing telemetry, evolving attack patterns, and cloud-provider differences. With systematic validation and responsible deployment, distributed AI learning and cross-domain event correlation can contribute to more efficient investigations, improved security coordination, and stronger resilience against sophisticated attacks targeting enterprise cloud infrastructure.

Future Work

Future research should focus on developing adaptive distributed learning models that can detect evolving cyber threats across heterogeneous cloud environments. Attackers continuously modify their techniques, exploit emerging vulnerabilities, and distribute malicious activities across multiple services to avoid detection by individual security systems. Models trained exclusively on historical datasets may therefore experience performance degradation when operational conditions or attack distributions change. Future studies could investigate federated continual learning, online anomaly detection, self-supervised representation learning, and incremental model updating to maintain detection effectiveness as new events become available. These approaches should be evaluated for their ability to identify



previously unseen attack patterns without introducing excessive false positives or destabilizing existing security operations. Graph neural networks represent another promising direction because they can model relationships among identities, endpoints, workloads, applications, and network connections. Temporal graph analysis could help reconstruct multistage attacks by examining how suspicious activities evolve across infrastructure domains. Researchers could also investigate causal inference methods to distinguish events that merely occur together from those that provide stronger evidence of a common attack process. Such distinctions are important because correlation alone does not establish causation. Future frameworks should incorporate uncertainty estimation, evidence provenance, and confidence-aware incident reconstruction to prevent misleading conclusions. Evaluation should include realistic attack simulations, historical incident traces, changing workloads, and previously unseen threat categories. Researchers should report model performance, computational requirements, adaptation time, and failure conditions to establish whether these advanced methods provide practical advantages over conventional approaches.

Another important research direction involves strengthening privacy, trust, scalability, and automation in distributed threat investigation. Federated learning and secure aggregation could support collaborative intelligence development without requiring participating organizations to transfer raw security logs. However, future work must examine model inversion, membership inference, poisoning attacks, malicious participants, and the potential disclosure of sensitive information through shared updates. Differential privacy and cryptographic protection may reduce some risks, although their computational costs and possible effects on detection quality require careful assessment. Interoperability should also be improved through standardized event representations, consistent identity resolution, secure timestamps, and well-defined intelligence exchange interfaces. At the operational level, future systems could integrate investigation results with security information and event management platforms, security orchestration and response tools, and cloud-native monitoring services. AI-assisted investigation agents could summarize correlated events, identify affected resources, recommend containment actions, and prepare incident reports. High-impact actions, such as disabling enterprise identities or isolating critical production workloads, should remain subject to clearly defined authorization policies and human approval unless a carefully validated policy explicitly permits automated execution. Additional research should examine how explainable AI can present evidence, uncertainty, and alternative interpretations in ways that support analyst decisions. Large-scale testing across multiple cloud providers, geographical regions, and administrative domains will be necessary to evaluate scalability, resilience, latency, and cost. Finally, reproducible benchmark datasets, standardized evaluation protocols, and independent validation should be developed to facilitate meaningful comparisons among competing approaches. These advances can help establish a secure, interpretable, and scalable foundation for cross-domain threat investigation in increasingly distributed enterprise cloud environments.

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