AI-Assisted Cyber Threat Intelligence Fusion Using Large Language Models and Knowledge Graphs

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Abstract

The fusion of heterogeneous cyber threat intelligence (CTI) sources into coherent, actionable knowledge remains a critical challenge for defensive cyber operations. Traditional approaches relying on rule-based correlation and manual analysis cannot scale with the volume, velocity, and variety of threat data. This paper presents a system-level examination of an AI-assisted CTI fusion architecture that integrates large language models (LLMs) and knowledge graphs (KGs) to enable automated extraction, normalization, and reasoning over threat indicators and adversary behaviors. We argue that the complementary strengths of LLMs in natural language understanding and KGs in structured semantic representation can be harnessed through a layered pipeline that includes ingestion, entity and relation extraction, graph construction, and query-based reasoning. However, such an architecture introduces significant structural trade-offs in terms of computational cost, latency, interpretability, robustness to adversarial manipulation, and alignment with existing threat intelligence standards. This paper explores these trade-offs from an interdisciplinary perspective, considering not only technical performance but also governance, policy, and socio-technical sustainability. Through conceptual analysis and illustrative case comparisons across domains such as financial fraud detection and healthcare data integration, we highlight the importance of modular design, human-in-the-loop oversight, and adaptive policy frameworks. We conclude by outlining future research directions that emphasize transparent AI models, federated threat sharing, and ethical safeguards for automated intelligence fusion.

Keywords

Cyber Threat Intelligence, Large Language Models, Knowledge Graphs, Information Fusion, Socio-Technical Systems, AI Governance.

1. Introduction

The modern cyber threat landscape is characterized by rapidly evolving attack vectors, sophisticated advanced persistent threat groups, and an ever-expanding attack surface driven by digital transformation. Effective defense requires the continuous collection, analysis, and dissemination of cyber threat intelligence, which encompasses indicators of compromise, tactics techniques and procedures, adversary infrastructure, and contextual narrative descriptions. However, threat intelligence is produced in a wide variety of formats ranging from structured indicators in STIX and TAXII to unstructured natural language reports, blog posts, and forum threads. Fusing these heterogeneous sources into a unified, machine-

readable, and actionable knowledge base is a longstanding problem that has resisted fully automated solutions.

Recent advances in large language models have demonstrated remarkable capabilities in understanding and generating natural language, while knowledge graphs have long provided a robust framework for representing structured relational information. The combination of these two technologies offers a promising path forward for CTI fusion: LLMs can parse unstructured text and extract entities and relationships, which are then integrated into a KG that supports querying, inference, and graph analytics. This paper presents a systematic architecture for such an AI-assisted fusion system, analyzing the design decisions and trade-offs that arise when deploying LLMs and KGs in an operational threat intelligence context.

The scope of this paper is deliberately system-level and interdisciplinary. Rather than focusing on isolated algorithmic improvements, we examine the entire pipeline from data ingestion to intelligence product generation, with attention to computational infrastructure, latency requirements, robustness against adversarial poisoning, interpretability of fusion results, and alignment with existing standards and governance frameworks. We also consider the socio-technical dimensions of deploying such systems within security operations centers, including the need for human oversight, trust calibration, and ethical use of automated analysis.

2. Background and Related Work

Cyber threat intelligence fusion has been approached from multiple angles. Rule-based correlation engines that map indicators to known attack patterns have been widely deployed but are brittle when faced with novel or obfuscated threats [1]. Machine learning methods, including classification and clustering of indicator features, have improved generalization but often sacrifice interpretability [2]. More recently, graph-based approaches that model relationships between threat entities have gained traction, leveraging techniques such as graph neural networks for threat detection [3]. However, these methods typically require a pre-existing structured graph and do not address the challenge of extracting structured knowledge from unstructured text.

Large language models, particularly transformer-based architectures, have transformed natural language processing tasks such as named entity recognition, relation extraction, and text summarization [4]. In the cybersecurity domain, LLMs have been applied to vulnerability description analysis, phishing detection, and even automated exploitation [5]. Their ability to process context-rich text makes them well-suited for extracting threat intelligence from reports and communications. Nevertheless, LLMs suffer from hallucinations, lack of persistent memory, and difficulty in maintaining consistent factual representations across long contexts [6].

Knowledge graphs provide a formal representation of entities and their relationships, enabling logical reasoning, graph traversal, and integration with ontologies. The use of KGs for CTI has been explored in projects such as ThreatKG and STUCCO, which construct graphs from structured indicator feeds and manual curation [7]. However, automated KG construction from text is non-trivial, requiring accurate entity linking and relation extraction. The combination of LLMs and KGs attempts to mitigate these limitations: LLMs can generate candidate knowledge triples, which are then verified and stored in a KG that supports querying and reasoning [8]. This synergy has been demonstrated in domains such as

biomedical research and question answering, but its application to cyber threat intelligence remains nascent.

Existing research on LLM-KG integration for CTI includes work on few-shot extraction of tactics and techniques from threat reports [9] and on building interactive threat intelligence assistants that combine retrieval augmented generation with graph databases [10]. These efforts highlight the potential but also reveal challenges in scaling to real-world data volumes and in ensuring that the extracted knowledge aligns with widely adopted standards such as the MITRE ATT&CK framework [11]. Our paper extends this body of work by providing a holistic system architecture and analyzing the structural trade-offs and governance implications that arise when such a system is deployed in a production environment.

3. Architectural Framework for AI-Assisted CTI Fusion

The proposed architecture is organized into four main layers: ingestion and preprocessing, entity and relation extraction, knowledge graph construction and storage, and query and reasoning services. The ingestion layer handles heterogeneous data sources, including structured feeds from threat sharing platforms, semi-structured documents such as STIX bundles, and unstructured text from open source intelligence, internal incident reports, and dark web forums. A preprocessing module normalizes formats, removes duplicates, and applies data quality filters to reduce noise and adversarial contamination. This layer must operate with high throughput and low latency to support near-real-time intelligence updates.

The extraction layer employs a large language model fine-tuned for cybersecurity named entity recognition and relation extraction. The LLM processes text chunks to identify entities such as IP addresses, domain names, malware hashes, file paths, and attacker groups, as well as relationships like “uses,” “targets,” or “communicates with.” The output is a set of triplets (subject, predicate, object) that are candidates for inclusion in the knowledge graph. Confidence scores are attached to each extraction to allow downstream filtering. A critical design decision is the choice of LLM: larger models with billions of parameters offer higher accuracy but incur greater computational cost and latency, while smaller models are faster but may miss subtle relationships. Trade-offs between accuracy, speed, and resource consumption must be evaluated based on the operational context, such as whether the system supports real-time alerting or batch analysis.

The knowledge graph construction layer takes the extracted triplets and integrates them into an existing graph database, typically using a property graph model. Entities are deduplicated through entity resolution techniques that use both textual and contextual features. Relations are enriched with temporal attributes, source provenance, and confidence scores. The KG is structured using an ontology aligned with the MITRE ATT&CK taxonomy and the STIX standard to ensure interoperability with other threat intelligence platforms. The graph can be updated incrementally as new data arrives, but the system must handle concurrent updates and ensure consistency. Reasoning capabilities are implemented through graph traversal algorithms that infer implicit relationships, such as linking a newly observed IP address to a known campaign based on shared infrastructure.

The query and reasoning layer provides interfaces for analysts to query the KG using natural language or structured query languages. LLMs can be used again to translate natural language questions into graph queries, or to summarize query results into readable threat reports. This layer also supports automated correlation rules that trigger alerts when certain graph patterns are detected, such as a new indicator connected to a known threat actor through a chain of

relationships. The overall architecture is modular, allowing each component to be replaced or upgraded independently, and includes a feedback loop where analysts can correct extraction errors, which are then used to fine-tune the LLM or update the KG's entity resolution rules.

4. Structural Trade-offs and System Design Considerations

Deploying an LLM-KG fusion system for CTI involves a series of structural trade-offs that affect performance, cost, and operational viability. One primary trade-off is between extraction accuracy and latency. Large language models with hundreds of billions of parameters can achieve state-of-the-art performance on named entity recognition and relation extraction benchmarks [12], but their inference latency on commodity hardware is often in the order of seconds per document. For threat intelligence feeds that generate thousands of documents per day, the total processing time can become hours, which may be unacceptable for time-sensitive threats. Smaller distilled models or domain-specific fine-tuned models can reduce latency to milliseconds while maintaining acceptable accuracy for most CTI tasks, but may miss subtle or rare indicators that a larger model would catch. Organizations must therefore assess their risk tolerance and the criticality of certain intelligence sources when selecting model size.

Another trade-off concerns the degree of automation versus human oversight. A fully automated pipeline that ingests data, extracts knowledge, and populates the KG without human intervention can achieve high throughput and scalability, but it also amplifies the risk of propagating errors, adversarial poisoning, or misinterpretation of ambiguous text. For example, an LLM might mistakenly extract a benign IP address as a malicious indicator because of a sarcastic phrase in a forum post. Such errors, once embedded in the KG, can contaminate downstream queries and alerts. A human-in-the-loop approach where analysts review and validate extracted triplets before they enter the graph reduces error propagation but introduces bottlenecks and increases operational costs. A middle ground is to use confidence thresholds and automated validation rules, flagging low-confidence extractions for human review while accepting high-confidence ones automatically. This hybrid approach balances speed with accuracy but requires careful tuning of confidence thresholds, which may vary across different types of entities and relationships.

The choice of knowledge graph model also presents trade-offs. Property graph databases like Neo4j offer flexible schema and fast traversal capabilities, but they lack built-in reasoning support for logical inference over OWL or RDF ontologies. Conversely, RDF stores with SPARQL querying support formal reasoning but are less performant for graph analytics tasks. For CTI fusion, a property graph augmented with a shallow ontology often suffices, but organizations that require complex reasoning about adversarial behaviors may benefit from a knowledge graph aligned with a formal ontology such as the Unified Cyber Ontology [13]. However, such alignment adds complexity to the extraction and integration pipeline, as the LLM must produce triples that conform to the ontology's constraints.

Robustness and security of the fusion system itself is a critical concern. Adversaries may attempt to poison the intelligence stream by injecting malicious content designed to mislead the LLM's extraction process or to create false associations in the KG. For instance, an attacker could post a fabricated threat report that links a legitimate domain to a known malware campaign, causing the system to generate false alerts or to attribute malicious activity to the wrong actor. Defenses against such attacks include source reputation scoring, cross-validation with multiple independent sources, and anomaly detection on graph patterns. Additionally, the LLM component is vulnerable to adversarial text inputs that cause it to

output incorrect extractions. Recent work has shown that LLMs can be manipulated with carefully crafted prompts or text perturbations [14]. Therefore, the fusion system must incorporate input sanitization and output verification mechanisms, which add overhead and may reduce throughput.

5. Deployment, Governance, and Policy Implications

Deploying an AI-assisted CTI fusion system within a real-world security operations center raises numerous governance and policy issues. The system must operate within legal frameworks that vary by jurisdiction regarding data privacy, incident reporting, and information sharing. For example, the extraction of personal data from threat intelligence reports, such as email addresses or employee names, may be subject to privacy regulations like the General Data Protection Regulation. The fusion pipeline must incorporate data anonymization or pseudonymization steps where necessary, and these steps must be auditable. Furthermore, the use of LLMs that are trained on internet-scale data introduces risks of exposing proprietary or sensitive information through model inversion or membership inference attacks. Organizations may need to deploy private, on-premises LLMs rather than relying on cloud-based APIs, which entails significant infrastructure investment and maintenance.

Another policy dimension is the need for transparency and explainability. Security analysts must trust the intelligence products generated by the fusion system, which requires that they understand how a particular conclusion was reached. While knowledge graphs inherently provide traceability because each fact is stored with provenance, the LLM-driven extraction process is often opaque. Recent research in explainable AI has proposed methods to generate natural language justifications for extractions, but these are not yet mature enough for operational use. Governance frameworks should mandate that the fusion system provide human-readable explanations for high-confidence alerts, and that analysts have the ability to override or correct automated decisions. This human oversight is essential not only for accuracy but also for accountability in case of erroneous intelligence leading to costly defensive actions.

The sharing of fused threat intelligence across organizational boundaries is a long-standing goal of the cybersecurity community. Standards like TAXII facilitate machine-to-machine exchange of indicators, but the fusion system’s output must be formatted into these standardized structures. Moreover, the KG itself could be shared partially or fully with trusted partners, but such sharing introduces challenges in access control, data provenance, and intellectual property protection. A federated approach, where each organization maintains its own KG and only shares anonymized summaries or query results, may be more viable than centralizing all intelligence into a single graph. This model aligns with privacy-preserving information sharing initiatives and can reduce the risk of exposing sensitive internal infrastructure.

Sustainability of the fusion system over time is another governance concern. The LLM component requires periodic retraining or fine-tuning to adapt to new threat terminology, techniques, and vulnerabilities. Maintaining an up-to-date training dataset is a significant effort that demands ongoing curation of labeled threat intelligence. The knowledge graph also needs continuous evolution, including merging with external threat feeds and removing obsolete indicators. These maintenance tasks require dedicated personnel with expertise in both cybersecurity and machine learning, which is a scarce resource. Policy decisions must

therefore allocate adequate funding and staffing for the long-term operation of the system, rather than treating it as a one-time deployment.

6. Case Illustrations and Cross-Domain Comparisons

To illuminate the practical implications of the architecture and trade-offs discussed, we consider illustrative cases from adjacent domains where LLM-KG fusion has been applied. In the financial sector, fraud detection systems use LLMs to extract transactional entities and relationships from unstructured reports, building KGs that model connections between accounts, transactions, and known fraud rings [15]. These systems face similar challenges of volume, adversarial manipulation, and the need for real-time processing. One key lesson from financial fraud detection is the importance of temporal reasoning: fraud patterns evolve quickly, and the KG must support temporal queries to identify trends and anomalies. This requirement translates directly to CTI, where the recency of indicators and the timeline of adversary operations are critical.

In the healthcare domain, LLM-KG fusion has been employed to integrate biomedical literature and electronic health records for decision support [16]. The emphasis there is on high precision due to the life-critical nature of the domain, leading to extensive human validation of extracted relationships. For CTI, a similar emphasis on precision is warranted for high-severity alerts, while lower-severity intelligence might tolerate lower precision. Healthcare applications also highlight the need for interoperability with existing ontologies such as SNOMED CT, analogous to the need for CTI systems to align with MITRE ATT&CK and STIX.

A cross-domain comparison reveals that the structural trade-offs we identified are common across all fields, but their relative importance shifts. In domains with high consequences of false positives, such as healthcare or military cyber operations, the trade-off favors accuracy over speed, and human oversight is non-negotiable. In commercial CTI environments where speed is paramount, such as for automated blocking of known malicious IPs, a fully automated pipeline with high recall may be acceptable. The governance and policy implications also vary: healthcare data is subject to strict privacy regulations that limit sharing, whereas threat intelligence sharing is often encouraged through public-private partnerships. Understanding these domain-specific nuances helps organizations tailor the fusion architecture to their unique operational context.

7. Conclusion

The integration of large language models and knowledge graphs offers a powerful approach to automating the fusion of heterogeneous cyber threat intelligence, enabling the extraction of structured knowledge from unstructured text and supporting scalable reasoning over complex relationships. However, the deployment of such AI-assisted systems is not merely a technical challenge; it involves careful navigation of structural trade-offs between accuracy, latency, autonomy, robustness, and governance. This paper has presented a layered architectural framework, analyzed key design decisions, and discussed the socio-technical implications of implementing such a system in practice.

Future research should focus on developing more efficient LLMs that can operate on edge devices within security appliances to reduce latency, and on robust adversarial training methods that protect against poisoning attacks. Explainability techniques for LLM-based extractions must advance to build analyst trust. On the governance side, policy frameworks for accountable AI in cybersecurity are urgently needed, including standards for auditing

automated intelligence generation and for ensuring equitable access to federated threat sharing networks. As the threat landscape continues to evolve, the fusion of LLMs and KGs will likely become an indispensable component of modern cyber defense, but its successful adoption depends on addressing these interdisciplinary challenges with rigor and foresight.

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