A Comprehensive View of Software Vulnerability Risks Through Enterprise Knowledge Graphs

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Abstract —The modern software supply chain's complexity, characterized by extensive dependencies and continuous integration/continuous deployment (CI/CD) pipelines, has rendered traditional, siloed vulnerability management systems inadequate. Cybersecurity data, including vulnerability reports, Software Bill of Materials (SBOMs), and asset inventories, reside in disparate formats and systems, hindering a unified risk perspective. This paper proposes and details a semantic approach to this challenge using an Enterprise Knowledge Graph (EKG). We present a Cybersecurity Ontology Network that provides a shared vocabulary for core concepts and relationships in software vulnerability management. We then describe an automated pipeline for converting heterogeneous data sources, such as Amazon Inspector reports, CycloneDX SBOMs, and relational asset databases, into a scalable EKG. The system is evaluated using a set of competency questions, demonstrating its efficacy in providing rapid, holistic insights into vulnerability exposure across the software ecosystem. By adopting this Data-Centric architecture, organizations can overcome the limitations of Application-Centric systems, achieving a flexible, FAIR (Findable, Accessible, Interoperable, Reusable), and future-proof framework for cybersecurity intelligence.

Keywords —Enterprise Knowledge Graph, Cybersecurity, Ontology, Software Vulnerability, SBOM, Semantic Web, Data-Centric Architecture, FAIR Principles.

1. Introduction

The digital transformation of enterprises has inextricably linked operational success to software integrity. However, this reliance has expanded the attack surface exponentially. The sophistication and volume of cyber threats—from ransomware and supply chain attacks to the exploitation of unpatched vulnerabilities—demand a more intelligent and integrated defense posture [1, 2]. A critical vulnerability in a single open-source library can propagate through dependencies, potentially compromising hundreds of applications within an organization [3].

The primary obstacle to effective defense is not a lack of data, but its fragmentation. Vulnerability scanners (e.g., Amazon Inspector, Tenable) produce JSON reports with proprietary schemas [4], dependency managers (e.g., NPM, Maven) output structured manifests, Software Bill of Materials (SBOM) standards like CycloneDX and SPDX offer standardized but distinct formats [5, 6], and critical context about asset ownership and criticality remains locked in relational databases and spreadsheets [7]. This "siloed" data landscape, typical of Application-Centric Architectures , forces analysts to perform manual correlation, a slow and error-prone process that delays mitigation and increases organizational risk [8].

A paradigm shift towards a Data-Centric Architecture is underway, where information systems are designed around unified data models rather than individual applications [9, 10]. At the forefront of this shift are Enterprise Knowledge Graphs (EKGs) . EKGs provide a powerful framework for integrating heterogeneous data by representing entities and their relationships in a machine-understandable format [11, 12]. When coupled with formal ontologies —which define a shared vocabulary and logical constraints—EKGs create a semantic layer that enables sophisticated reasoning and querying [13].

While prior research has explored knowledge graphs for cybersecurity, the focus has often been on intrusion detection [14], malware analysis [15], or threat intelligence [16]. The specific domain of software vulnerability management , particularly the semantic integration of SBOMs, vulnerability reports, and software asset contexts, has not been sufficiently addressed [17, 18]. Existing ontologies like the Unified Cybersecurity Ontology (UCO) [19] provide a broad foundation but lack depth in representing the intricate relationships of software packages and their bill of materials.

Contributions of this work are threefold:

1. We present a Cybersecurity Ontology Network that extends existing standards to comprehensively model software components, vulnerabilities, and their dependencies.
2. We design and implement an automated data pipeline that ingests diverse sources (CycloneDX SBOMs, Inspector scans, relational data) to construct a scalable EKG for vulnerability management.
3. We demonstrate the practical utility of the system through competency questions and SPARQL queries, showing how it provides a comprehensive view of vulnerability risk, directly supporting threat modeling and operational decision-making at Siemens Energy.

2. Literature Review

2.1. The Limitation of Siloed Cybersecurity Data

The challenge of data silos in cybersecurity is well-documented. [20] highlights how isolated security tools create visibility gaps, while [21] emphasizes the operational inefficiency of context-switching between consoles. The reliance on manual correlation is identified as a significant source of "alert fatigue" and slow mean-time-to-respond (MTTR) [22]. The move towards SBOMs, driven by both industry best practice and regulatory pressure (e.g., U.S. Executive Order 14028 [23]),, while beneficial, introduces a new data source that must be integrated to be actionable [24].

2.2. Knowledge Graphs and Ontologies in Cybersecurity

Knowledge Graphs have proven their value in integrating complex information. Their application in cybersecurity is a growing field of research.

Ontologies: Several ontologies provide a semantic foundation. The Unified Cybersecurity Ontology (UCO) [19, 25] is a leading effort to integrate standards like STIX [26], CVE [27], CWE [28], and CAPEC [29]. Other ontologies focus on specific domains, such as the Internet of Things (IoTSec) [30] or network reachability [31]. However, as noted in a systematic review by [17], creating a generic and extensible cybersecurity ontology remains challenging, and many lack the granularity for detailed software composition analysis.

Knowledge Graphs in Practice: EKGs have been applied to various cybersecurity tasks. [32] used a KG for IT risk assessment, [14] for cyber-attack detection, and [33] for uncovering relationships between CWE, CVE, and CPE. Large Language Models (LLMs) are also being explored to generate [34] or enrich cybersecurity KGs [35]. A recent review by [18] confirms that the primary focus of cybersecurity KGs has been on threats and attack patterns, with the connections between software packages, libraries, and vulnerabilities being an under-explored area.

2.3. The Gap in Software Vulnerability Management

Initial ontology efforts for vulnerability management, such as [36], did not adequately address software libraries and SBOMs. Later works, including [37], and models for software defects like [38], often focused on single aspects. The critical need is for a holistic system that can answer questions like: "Given this new CVE, show me all deployed services owned by the 'Payment' team that use a vulnerable version of `log4j`, and rank them by business criticality." Answering this requires a unified view that current siloed systems and most research prototypes cannot efficiently provide. Our work directly addresses this gap by leveraging the EKG paradigm to create a unified, semantic layer for software vulnerability risk.

3. Methodology: Building the Vulnerability Knowledge Graph

Our approach is built on a semantic technology stack and follows a structured process to transform raw, disparate data into an insightful knowledge graph.

3.1. The Cybersecurity Ontology Network

Our ontology network serves as the foundational schema for the EKG. It is designed to be interoperable with existing standards while providing the specificity needed for software vulnerability management.

Core Concepts: The ontology defines key classes such as `SoftwareComponent`, `Version`, `Vulnerability` (linked to CVE IDs), `Project`, `Team`, and `Asset`. It also models crucial relationships like `hasDependency`, `hasVulnerability`, `isOwnedBy`, and `isDeployedOn`.

Alignment with Standards: The ontology is explicitly aligned with the CycloneDX standard for SBOMs [5], ensuring it can natively represent component hierarchies, hashes, and suppliers. It also imports and extends concepts from UCO [19] to maintain compatibility with broader cybersecurity concepts and from vocabularies like DOAP (Description of a Project) for project metadata.

Semantic Richness: By using OWL (Web Ontology Language) [39], we can define logical constraints. For example, we can assert that a `Vulnerability` can only affect a `SoftwareComponent`, and that the `cvssScore` must be a float. This enables a level of data validation and consistency checks that are impossible in siloed systems.

3.2. Data Ingestion and Integration Pipeline

The pipeline is responsible for the EKG's population and maintenance. Its architecture is outlined in Figure 1.

1. Data Extraction: Connectors pull data from the source systems:

   SBOM Sources: CI/CD pipelines generate CycloneDX SBOMs for every build.

   Vulnerability Scanners: JSON reports from tools like Amazon Inspector [4] are ingested.

   Asset & Project Repositories: Data from CMDBs (Configuration Management Databases), GitHub, and Jira is extracted via APIs or SQL queries.
2. Data Transformation & Mapping: This is the critical step where heterogeneous data is mapped to the ontology. Custom scripts (e.g., in Python) convert source JSON, CSV, and relational data into RDF (Resource Description Framework) triples [40]. For example, a `component` in a CycloneDX file becomes an instance of `SoftwareComponent`, and its `bom-ref` is used as a unique URI.
3. Graph Population: The generated RDF triples are loaded into a triplestore (e.g., Ontotext GraphDB, Stardog) which materializes the EKG. The triplestore's reasoner can infer new knowledge based on the ontology's logical rules, enriching the graph without explicit data entry.

3.3. Data Storage and Consumption

The populated EKG is stored in a scalable triplestore that supports SPARQL 1.1 [41]. SPARQL is the standard query language for KGs and is used for all data consumption.

Front-end Applications: Custom dashboards can be built that issue SPARQL queries to power visualizations, such as dependency trees colored by vulnerability severity.

Analyst Queries: Security analysts can write or use pre-defined SPARQL queries to investigate complex scenarios interactively.

API Integration: The triplestore can expose a SPARQL endpoint, allowing other security applications (e.g., SIEMs, SOAR platforms) to query the EKG for contextual information.

4. Evaluation and Results

4.1. Competency Questions

The system was evaluated against a set of competency questions (CQs)—natural language questions that the EKG must be able to answer [42]. These CQs were defined in collaboration with cybersecurity analysts at Siemens Energy to ensure practical relevance.

CQ1: Which projects and their responsible teams are using a specific version of a library (e.g., `spring-core 5.3.18`) that has a known critical vulnerability (CVSS score > 9.0)?

CQ2: For a newly published CVE (e.g., CVE-2021-44228), what are all the deployed assets that are affected, and who are the owners of those assets?

CQ3: List all transitive dependencies of a specific application that contain vulnerabilities, and visualize the attack path from the application to the vulnerable dependency.

CQ4: Identify all libraries across the organization that are no longer maintained and have at least one unpatched vulnerability.

4.2. SPARQL Query Example

The following simplified SPARQL query demonstrates how CQ1 is executed against the EKG.

```sparql
PREFIX sec: <http://www.siemens-energy.com/cybersecurity       >
PREFIX cve: <http://cve.mitre.org/cve/>

SELECT ?projectName ?teamName ?componentVersion WHERE
{
  ?vul a sec:Vulnerability .
  ?vul sec:hasCVEId "CVE-2022-22965" .
  ?vul sec:hasCVSSScore ?score .
  FILTER (?score > 9.0)

  ?component sec:isAffectedBy ?vul .
  ?component sec:hasName "spring-core" .
  ?component sec:hasVersion ?componentVersion .

  ?project sec:usesComponent ?component .
  ?project sec:hasName ?projectName .
  ?project sec:isOwnedBy ?team .
  ?team sec:hasName ?teamName .
}
```

Result: This query would return a table listing all projects, their teams, and the specific version of `spring-core` they use that is vulnerable to CVE-2022-22965 (a critical Spring4Shell vulnerability), enabling rapid, targeted communication and patching.

4.3. The Resulting Knowledge Graph

The implemented EKG at Siemens Energy integrates data from over 15,000 software components, 50,000 unique vulnerabilities, and hundreds of projects. The graph contains several hundred million RDF triples. The key result is not the graph's size, but its connectedness; it creates a unified fabric of knowledge that was previously inaccessible, reducing the time for vulnerability impact analysis from hours or days to seconds.

5. Discussion

The migration from an Application-Centric to a Data-Centric architecture via an EKG is not without challenges. Key decisions and observations from our project include:

Ontology Design is Critical: The initial ontology design required several iterations. Engaging domain experts (security analysts, software architects) early was crucial for capturing the correct relationships and attributes. Future work will involve a more formal ontology evaluation.

Data Quality is a Prerequisite: The EKG exposed underlying data quality issues in source systems (e.g., missing component versions, outdated asset records). The EKG project thus acted as a catalyst for improving data governance across the organization.

Performance at Scale: Query performance for complex traversals (e.g., finding all transitive dependencies) can be a bottleneck. We addressed this through strategic use of SPARQL property paths, triple store indexing optimization, and, in some cases, materializing often-requested paths.

The FAIR Advantage: The resulting infrastructure inherently adheres to FAIR principles [43]. Vulnerability data is Findable via rich metadata and relationships, Accessible through a standard SPARQL endpoint, Interoperable due to the ontology-based model, and Reusable for various analytical purposes beyond its original design.

This approach represents a significant advancement over traditional methods. It moves vulnerability management from a reactive, component-focused activity to a proactive, system-wide risk assessment capability.

6. Conclusion and Future Work

This paper has presented a comprehensive, ontology-driven approach to managing software vulnerability risks using an Enterprise Knowledge Graph. By unifying SBOMs, vulnerability reports, and asset data under a shared semantic model, we have demonstrated a practical path for organizations to gain a holistic and immediate understanding of their exposure.

The implemented system at Siemens Energy provides compelling evidence that EKGs can overcome the critical data integration challenges that plague modern cybersecurity operations. The use of competency questions and SPARQL queries validates the system's ability to deliver actionable intelligence with unprecedented speed and context.

Future work will focus on several areas:

1. Predictive Analytics: Leveraging graph neural networks (GNNs) on the EKG to predict the likelihood of a vulnerability being exploited based on the attributes of the component and its network position [44, 45].
2. LLM Integration: Exploring the use of Large Language Models to enable natural language querying of the EKG, making it more accessible to non-technical stakeholders [46, 47].
3. Real-time Stream Processing: Enhancing the pipeline to support real-time ingestion of new CVEs and SBOM updates, moving the organization closer to continuous, real-time threat assessment [48].
4. Expanding Scope: Extending the ontology and graph to incorporate additional data sources, such as threat intelligence feeds (STIX) [26] and cloud security posture management (CSPM) findings, to create a truly enterprise-wide cybersecurity knowledge base [49, 50].

In an era of escalating software supply chain threats, the ability to connect the dots through a unified knowledge fabric is not just a technological advantage—it is a strategic imperative.

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