Methodology

JDMS

Journal of Defense Modeling and Simulation: Applications, Methodology, Technology
1–16

DOI: 10.1177/15485129261435210
journals.sagepub.com/home/dms
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# A scalable ontology-driven architecture for situational awareness and decision support in multi-domain operations

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**Abstract**

Creating coherent and explainable *situational awareness* (SA) in multiple operational domains remains a persistent challenge for modern *command-and-control* (C2) systems. Heterogeneous data sources, inconsistent semantics, and fragmented reasoning mechanisms hinder timely and accountable decision-making in *multi-domain operations* (MDOs). This paper presents the design of a scalable, *ontology-driven architecture* that unifies data ingestion, semantic integration, and predictive reasoning within a modular framework for SA and decision support. The architecture employs an ontology-centric semantic core to ensure interoperability and traceability across domains while maintaining a clear separation between the data, reasoning, and analytics layers. Each component is motivated by operational and cognitive requirements, with an emphasis on scalability, explainability, and integration readiness. A conceptual *integration and validation path* is outlined to guide future evaluation within synthetic and simulation-based environments such as High Level Architecture (HLA) federations and C2 Systems—Simulation Systems Interoperation Standard (C2SIM) ecosystems. Rather than reporting empirical results or system-level performance metrics, the paper offers a theoretically grounded, design-oriented contribution, explicitly positioned as a methodological and architectural framework at an early stage of technological maturity.

**Keywords**

Situational awareness, multi-domain operations, ontology-driven systems, decision support, semantic interoperability, simulation interoperability, HLA, C2SIM

## 1. Introduction

The increasing complexity of contemporary operational environments has led armed forces and defense organizations to adopt *multi-domain operations* (MDOs) as a core doctrinal and technological paradigm.[1–3] Traditional single-domain approaches, optimized for independent operations in land, air, maritime, or cyberspace, are no longer adequate to cope with the intertwined and rapidly evolving dynamics of modern warfare.[4] Each domain exhibits different operational tempos, sensing capabilities, and vulnerabilities, but their interdependence—particularly across information, energy, and decision layers—creates cascading effects that challenge timely coordination and shared situational understanding.[5] These interactions produce a multidimensional, data-dense operational environment, requiring architectures capable of maintaining semantic coherence and interoperability across heterogeneous systems.

The cognitive, physical, and virtual dimensions of MDO amplify this complexity and call for advanced *situational awareness* (SA) systems that can integrate, analyze, and disseminate multi-source information at high velocity. Conventional SA tools are typically limited to single-domain use and rely on static data fusion pipelines that cannot adapt to the volatility of cross-domain operations.[6,7] As a result, they struggle to produce actionable insights that support synchronized decision-making across

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distributed echelons. Recent research emphasizes that cross-domain resilience and mission effectiveness depend on both the fidelity of integrated data and the semantic interoperability of analytical layers.[8] This aligns with the doctrinal view that future operations will hinge on the ability to seamlessly orchestrate data and capabilities across domains rather than within them.[9]

However, several persistent limitations constrain the operational adoption of current SA frameworks in multi-domain contexts:

- *Data silos and integration deficits*. Existing systems often operate on isolated domain-specific data sets, producing fragmented analyses that hinder a shared operational picture. Semantic misalignment across domains—especially between tactical and strategic echelons—further weakens real-time cross-domain coherence.[10,11]
- *Limited adaptability and responsiveness*. The dynamic nature of MDO requires systems capable of re-prioritizing data sources and analytical focus in response to situational changes. Rigid architectures and pre-defined processing pipelines impede timely adaptation to evolving operational demands.[7]
- *Scalability under heterogeneous and high-velocity data flows*. The exponential increase in sensing modalities—from ISR to open-source intelligence—challenges existing architectures to maintain throughput and accuracy.[8] This calls for scalable information-fusion layers grounded in semantic consistency.
- *Deficiencies in proactive and predictive reasoning*. Many SA systems remain reactive, focusing on near-real-time visualization rather than forecasting likely evolutions of the operational environment. Predictive reasoning that links causal dependencies across domains remains underdeveloped.[12]

These gaps underscore the need for a scalable, semantically integrated architecture that bridges heterogeneous data sources, supports ontological reasoning, and enables predictive modeling of evolving operational states. While several nations have explored conceptual MDO frameworks, there remains limited architectural formalization of how such systems could ensure semantic interoperability, data scalability, and explainability within a single framework.[13,14] This paper addresses this gap by proposing a modular *ontology-driven system architecture* that enhances SA and decision support across all operational domains. It is important to clarify the scope of this contribution from the outset. This paper is intentionally positioned as a methodological and architectural study aimed at formalizing a scalable design framework for ontology-driven SA in MDOs, rather than evaluating a specific system implementation. Accordingly, the focus is placed on architectural principles, design rationale, and integration trade-offs, while empirical performance assessment and operational testing are explicitly considered out of scope at this stage of research (Technology Readiness Level (TRL) 1–2).

### 1.1. Research objectives and contribution

The objective of this study is to outline a theoretically grounded, scalable framework that integrates ontological reasoning with data ingestion and predictive analytics in MDO contexts. The proposed architecture is designed to (1) harmonize multi-source information through a unified semantic layer, (2) maintain explainability and traceability through ontology-based reasoning, and (3) ensure integration readiness with simulation-based validation environments compliant with High Level Architecture (HLA)[15,16] and C2 Systems—Simulation Systems Interoperation Standard (C2SIM) standards.[17,18] The design emphasizes modularity and scalability, enabling incremental evolution toward distributed and AI-enhanced systems.

The contribution of this work lies in articulating how these elements can be combined into a unified architecture that treats semantic interoperability as a structural property rather than an implementation detail. Whereas existing approaches often address ontology management, data fusion, predictive modeling, or simulation interoperability in isolation, this study integrates them into a single conceptual framework in which the ontology functions as the central organizing mechanism. This perspective clarifies the role of ontological knowledge in coordinating data pipelines, constraining predictive components, and supporting cross-domain reasoning, thus offering a coherent basis for interoperable and explainable decision support in multi-domain settings.

Rather than reporting empirical performance metrics or validating a specific instantiation, this paper focuses on articulating the architectural rationale underpinning the proposed system and discussing how such an architecture can be conceptually validated within established modeling and simulation (M&S) paradigms. The path leverages agent-based and federated modeling frameworks for progressive conceptual validation,[17] providing a foundation for subsequent prototyping and simulation-based evaluation.

## 2. Background and related work

The integration of artificial intelligence, semantic technologies, and M&S methods has recently renewed the debate on how to achieve coherent and explainable *SA* across multiple operational domains. This section outlines the main conceptual and technological strands relevant to the proposed architecture: doctrinal developments in MDO, advances in SA systems and information fusion, and ontology-based approaches for decision support and interoperability.

## *2.1. MDOs and SA*

The concept of MDOs has evolved from joint and combined warfare toward a data-centric and cognitively integrated framework.[10,13,14,19] Across national doctrines, MDO is conceived as the coordinated employment of military capabilities across land, air, maritime, space, and cyberspace domains to generate *convergence* effects.[2] However, convergence can only be achieved when a common situational picture is maintained across heterogeneous command structures and temporal scales. This requirement has increased interest in scalable SA architectures capable of processing massive, rapidly changing information flows and propagating shared understanding in near-real time.

From a cognitive standpoint, Endsley's seminal model[20,21] remains the most influential reference, defining SA as a three-level process encompassing perception, comprehension, and projection. Although originally developed for individual operators, subsequent studies have extended it to distributed and networked settings. In MDO, each level corresponds to distinct computational challenges: data acquisition and perception across domains (Level 1), semantic integration and reasoning (Level 2), and predictive analysis for forecasting potential evolutions (Level 3). Recent doctrinal publications emphasize that achieving these levels at scale requires architectures that combine automation, semantic transparency, and human oversight.[4]

## *2.2. Information fusion and data-centric architectures*

Information fusion has long been recognized as a key enabler for SA in dynamic and uncertain environments. Classic formulations distinguish between low-level sensor fusion and high-level situation assessment.[22,23] However, as operational environments grow more complex, the challenge has shifted from pure data fusion to the harmonization of heterogeneous and context-dependent information sources. Li et al.[8] provide a comprehensive survey of multisource fusion methods and highlight future research directions toward hybrid AI and human–machine integration for decision support. Their conclusions resonate with current MDO requirements, where data velocity, modality diversity, and semantic consistency must be jointly managed. Other works emphasize the importance of adaptive fusion mechanisms that can dynamically prioritize information streams based on mission context or threat evolution.[6]

At the architectural level, modern defense information systems increasingly adopt modular, service-oriented frameworks that separate ingestion, reasoning, and visualization layers. Yet, few of these architectures explicitly address the semantic alignment problem, which becomes critical when integrating sensor, textual, and cognitive data in a single decision loop.[24] This limitation motivates the introduction of ontology-based structures that can formalize relationships among entities, actions, and domains while supporting interoperability with M&S tools.

## *2.3. Ontology-based reasoning and semantic integration*

Ontologies have proven effective in enabling semantic interoperability and improving interpretability in complex systems. Early applications in the defense M&S domain have already demonstrated their value for structuring SA processes: for example, Nagle et al.[25] showed how an ontological representation of entities and relations could support SA in simulation-based scenarios, enabling explicit reasoning about contextual dependencies and improving the coherence of situation assessment.

Building on this foundation, pioneering works by Kokar et al.[26] formalized ontology-driven representations for situation assessment through logical inference, allowing explicit modeling of causal and relational structures. Subsequent research expanded this approach to distributed SA systems and domain-specific ontologies for air and space traffic management.[27] In these frameworks, ontologies serve not only as structured knowledge repositories but also as reasoning substrates that enable explainable AI behavior.

Ontology-based modeling also supports the convergence between decision-support and simulation systems. By linking structured data to semantic schemas, models can be reused across analytical, predictive, and training environments. This aligns with recent interoperability studies showing that semantic grounding facilitates cross-system validation and composability.[9,17] The integration of ontologies with machine learning has further advanced through ontology embedding techniques, enabling hybrid neuro-symbolic reasoning.[28,29] Such methods demonstrate that semantic priors can improve robustness and interpretability without compromising scalability.

## *2.4. Interoperability and simulation-based validation*

Interoperability remains a foundational requirement within the defense M&S community. Standards such as the HLA[16] and the C2SIM[18] provide the formal mechanisms through which heterogeneous systems can exchange information across technical, structural, and semantic layers. These standards support not only data consistency but also the composability of distributed components, enabling complex federations to function as coherent analytical environments. Agent-based simulation has similarly been employed to assess interoperability and emergent behavior in distributed architectures, demonstrating its effectiveness as a testbed for evaluating system-level interactions.[17]

Beyond interoperability concerns, simulation environments increasingly contribute to the development and assessment of SA capabilities. Recent work has shown that advanced simulation architectures—including parallel and multi-objective simulation frameworks—can enhance SA in high-tempo or information-dense operational settings.[30] These findings underscore the need for scalable, semantically grounded mechanisms that enable SA components to operate within distributed M&S ecosystems while preserving coherence across domains.

Further studies link semantic modeling to operational planning and predictive reasoning. For instance, Wu et al.[12] demonstrate how ontology-driven task representations can support course-of-action generation and forecasting in complex scenarios, highlighting the role of structured semantic information in maintaining logical consistency across planning and predictive processes. Taken together, these contributions provide a strong theoretical foundation for combining ontology-centric reasoning with simulation-based validation to assess the scalability, interpretability, and cross-domain coherence of the proposed architecture.

### 2.5. Gap and rationale

Despite significant progress, most existing approaches remain limited to either specific domains or experimental prototypes. Few architectures provide a unified semantic layer that integrates heterogeneous data ingestion, ontological reasoning, and predictive analytics in a modular, scalable manner. Moreover, the literature often treats interoperability as a post hoc integration problem rather than as an inherent design principle. This paper addresses these gaps by presenting an ontology-centered architecture explicitly conceived to sustain explainable, cross-domain SA and to enable future validation through simulation-based federations.

## 3. System architecture

The proposed system architecture is designed as a scalable, ontology-driven framework for achieving explainable and interoperable *SA* in MDO. Rather than representing a single monolithic system, it defines a conceptual blueprint that guides the design of modular, interoperable *components, functional modules, and services* aligned with existing standards and simulation frameworks. The architecture supports both real-time decision support and simulation-based validation by structuring the data flow from collection to reasoning and prediction through a coherent semantic layer.

For clarity, the following terminology is adopted throughout this section. *Layers* denote the four functional levels of the architecture that organize information processing and decision-support logic. The components represent the core entities that implement semantic reasoning, data management, and predictive functions within those layers. *Modules* correspond to peripheral or I/O subsystems responsible for data acquisition, transformation, or dissemination. Finally, *services* refer to software mechanisms that enable communication or synchronization across layers, such as APIs and gateways. This distinction ensures terminological consistency and reflects the hierarchical design principles that underpin the overall system.

### 3.1. Architectural principles and design goals

The design follows four core principles derived from the operational and cognitive requirements listed in the previous sections:

- *Semantic coherence across domains*. Ontologies provide a unifying semantic representation of entities, actions, and relationships, ensuring consistent meaning across heterogeneous data sources.[26]
- *Layered modularity*. The architecture follows a modular, hierarchical design in which data management, semantic reasoning, predictive analytics, and dissemination are encapsulated in loosely coupled functional layers. This organization supports scalability, technology substitution, and parallel development, ensuring that each layer and its associated components can evolve independently while maintaining semantic coherence across the system.
- *Explainability and traceability*. Ontology-based reasoning and rule-based inference enable inspection of the logical chain from the input to the prediction, thereby improving interpretability and trust.[28]
- *Integration readiness*. Each *component and module* is designed for interoperability with simulation and C2 environments via open standards such as the IEEE *HLA*[15,16] and NATO's *C2SIM* standard.[17,18]

These principles provide the conceptual foundation for a system that can progressively evolve from research prototypes to deployable architectures in operational contexts.

### 3.2. Layered system overview

Building on the modular principles outlined above, the architecture (Figure 1) is instantiated through four functional *layers* that transform raw data into semantically grounded, predictive, and human-interpretable outputs. Each layer interacts through standardized *services and*

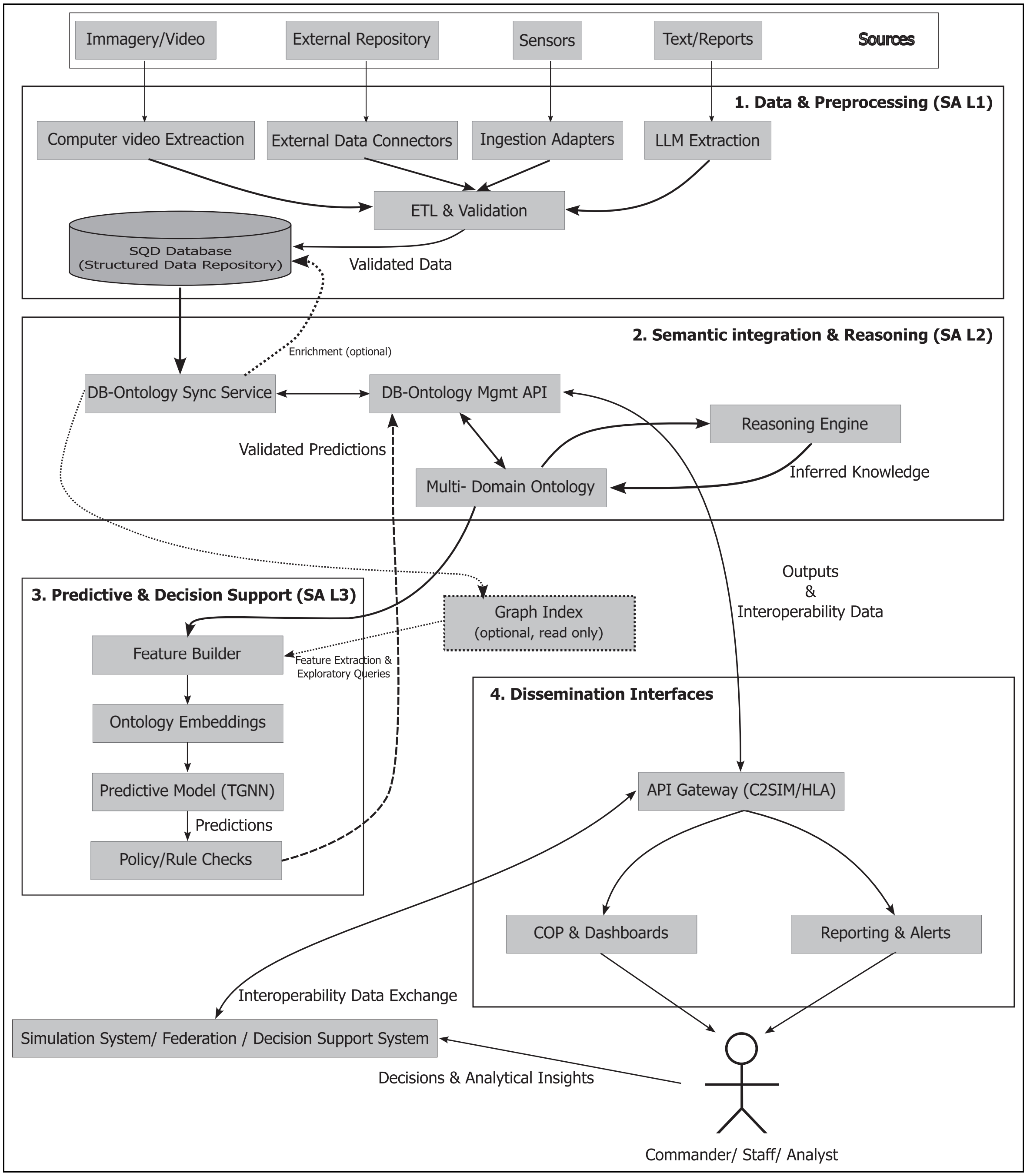


**Figure 1.** Overview of the proposed ontology-driven architecture for situational awareness, showing key components, modules, and services, including semantic synchronization and feedback mechanisms.

*interfaces* that preserve scalability and semantic alignment with the central ontology.

1. *Data and Preprocessing Layer*. Manages ingestion from heterogeneous sources (sensors, text, imagery, external repositories) via specialized *modules and services* (*Ingestion Adapters*, *LLM Extraction* for unstructured text, *Computer Vision Extraction* for images/video, *External Data Connectors* for third-party feeds). Data are standardized through an *ETL*

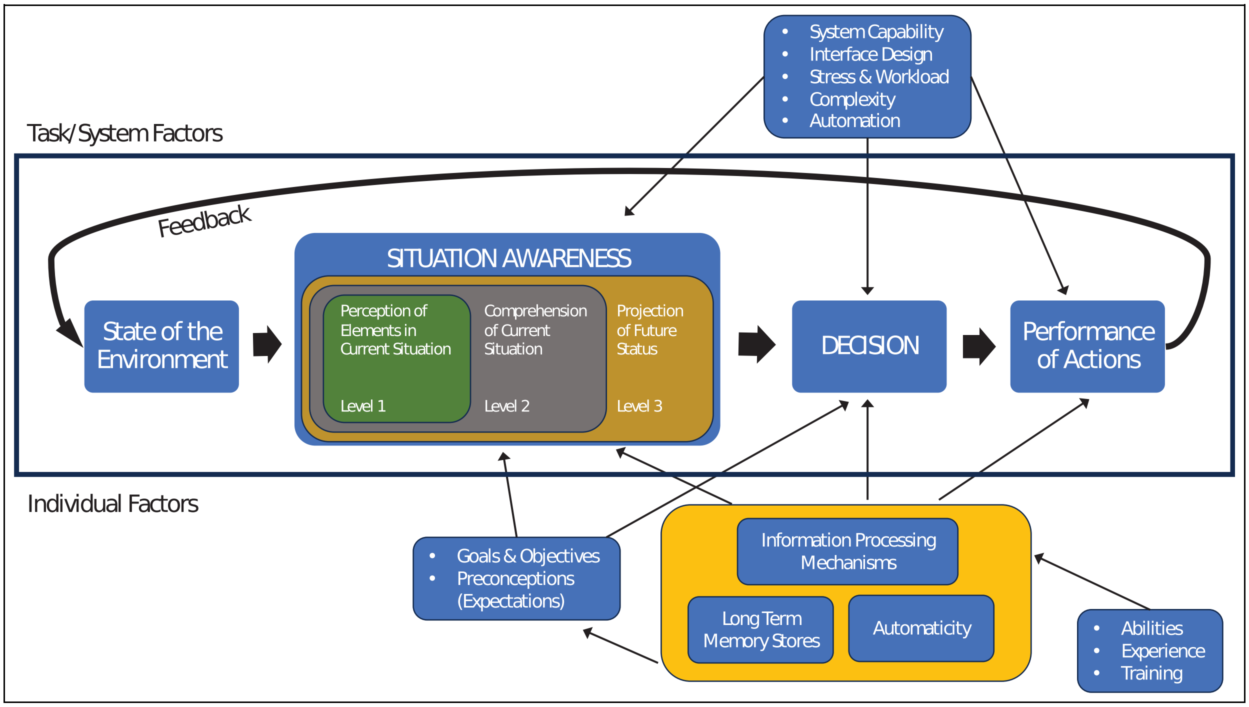


**Figure 2.** Conceptual representation of Endsley's model of situational awareness,[20] highlighting the three levels of situational awareness.

*(Extract–Transform–Load) & Validation* Pipeline and persisted in a structured repository for downstream semantic integration.

2. *Semantic Integration and Reasoning Layer*. Represents the system's core, where all entities and relations are instantiated in the Multi-Domain Ontology. This layer supports logical reasoning, causal inference, and context propagation across domains through the combined action of core *components and services:* the Ontology Management API, the DB–Ontology Sync Service, and the Reasoning Engine.
3. *Predictive and Decision-Support Layer*. Implements hybrid neuro-symbolic *components* that forecast system states, detect anomalies, and suggest courses of action. Predictions are validated through rule-based checks and reintegrated into the ontology to maintain semantic consistency and traceable provenance.
4. *Dissemination Interface Layer*. Delivers structured outputs to dashboards, reports, and simulation gateways, forming the human–machine interaction layer and ensuring interoperability with decision-support and modeling environments.

Together, these tiers implement the functional progression from perception (Level 1 SA) to comprehension (Level 2 SA) and projection (Level 3 SA), as defined in Endsley's model of SA (Figure 2).[20]

### 3.3. Core components

The following subsections describe the core *components* that implement the architecture's semantic reasoning and predictive capabilities. Together, they form the internal backbone that transforms standardized data into interpretable, ontology-based knowledge.

*3.3.1. Multi-Domain Ontology.* At the center of the architecture lies the *Multi-Domain Ontology*, which formalizes entities, relationships, and metrics relevant to the operational environment. It integrates conceptual structures from the physical, cyber, and cognitive dimensions of MDO.[31] The ontology enables semantic queries, automated classification, and inference through description logic reasoning. Its modular design allows for the extension to domain-specific ontologies (e.g. maritime, air, and cyber) without compromising global consistency.

*3.3.2. SQL database (Structured Data Repository).* The *SQL database*, serving as the architecture's Structured Data Repository, provides the authoritative, persistent backbone for preprocessed information. It provides transactional integrity, indexing, and predictable query performance and is synchronized with the ontology through dedicated agents. Optionally, a *Graph Index (read-only)* can be materialized from the SQL store to accelerate exploratory queries and neighborhood lookups; semantic alignment and reasoning remain the responsibility of the ontology layer rather than the Graph Index. This separation avoids redundancy while preserving efficient access paths for both transactional and semantic workflows.

*3.3.3. Reasoning and Inference Engine.* The *Reasoning and Inference Engine* operates over the ontological layer to derive implicit relationships, validate data consistency, and propagate contextual effects. By using rule languages and probabilistic extensions, it can model causal dependencies and uncertainty propagation, complementing the deterministic reasoning supported by standard ontology frameworks.[28] This capability transforms static knowledge into actionable insights while maintaining logical transparency.

*3.3.4. Predictive Model (TGNN).* The *Predictive Model* provides data-driven forecasting of future operational states. Ontology-informed embeddings are supplied as structured inputs to a temporal graph neural network (TGNN), combining the adaptability of deep learning with the interpretability of ontological reasoning.[12,29] The choice of a TGNN is motivated by the need to jointly model temporal dependencies and relational structures across domains, which are naturally represented in the ontology as evolving graphs. Alternative predictive approaches (e.g. time-series models or purely statistical learners) were considered less suitable at this architectural level, as they do not natively preserve relational semantics or support tight integration with ontology-driven reasoning. Model outputs undergo *Policy and Rule Checks*, which verify alignment with operational constraints and semantic consistency. Validated predictions are reinserted into the ontology through the Ontology Management API, ensuring bidirectional synchronization and maintaining traceable provenance of each inferred state.

## 3.4. Functional modules and services

Beyond the core reasoning and predictive components, the architecture incorporates *functional modules* and *services* that enable data acquisition, semantic synchronization, dissemination, and feedback. Their organization follows the functional logic represented in Figure 1.

*3.4.1. Acquisition and transformation modules.* These modules manage the end-to-end ingestion and normalization of heterogeneous data prior to semantic integration. *Ingestion Adapters*, *LLM Extraction*, *Computer Vision Extraction*, and *External Data Connectors* handle structured, textual, visual, and third-party inputs, respectively. They normalize metadata, timestamps, and attributes, passing standardized records to the *ETL and Validation Pipeline*, which implements the *ETL* process with schema and quality checks. Raw inputs are loaded into the Structured Data Repository and subsequently transformed into ontology-ready records, while validation ensures the completeness, consistency, and traceability of provenance before semantic reasoning.

*3.4.2. Semantic management services.* These services maintain alignment between factual data and the semantic layer, ensuring that reasoning and predictive components operate on a coherent, up-to-date knowledge base. The *Ontology Management API* provides northbound and southbound endpoints for creating, updating, and querying ontology individuals and axioms. It supports create, read, update and delete (CRUD) and reasoning operations for both the reasoning engine and the predictive layer and acts as the main entry point for reinserting validated predictions. Complementing it, the *DB–Ontology Sync Service* maintains bidirectional synchronization between the Structured Data Repository and the Multi-Domain Ontology, enforcing schema alignment and persistent identifiers so that symbolic knowledge and factual data remain consistent across layers.

*3.4.3. Predictive feature construction, validation, and reinsertion modules and services.* Within the predictive and decision-support layer, these modules and services implement the neuro-symbolic processing chain that links ontological reasoning with data-driven inference. The *Feature Builder Module* aggregates entity attributes, temporal relations, and cross-domain dependencies extracted through the Ontology Management API and, when available, the optional Graph Index. It converts semantically grounded knowledge into structured tensors suitable for model ingestion, while preserving ontological identifiers to ensure full traceability between symbolic and learned representations. The *Ontology Embeddings Service* encodes entities and relations into continuous vector spaces aligned with the Multi-Domain Ontology, enabling the TGNN to operate over a semantically coherent latent space. This service maintains consistency with ontology updates by synchronizing with the DB—Ontology Sync Service, ensuring that feature vectors remain aligned with the evolving knowledge base. The *Policy and Rule Check Module* validates TGNN predictions against ontological constraints, mission rules, and operational policies and filters out inconsistent or implausible outputs before reintegration. Finally, the

**Table 1.** Functional layers of the ontology-driven architecture and corresponding components, modules, and services.

| Layer | Main functions | Representative components/modules/services |
|---|---|---|
| Data and Preprocessing Layer | Acquisition, normalization, and validation of heterogeneous data before semantic integration. | **Components**: SQL Database (Structured Data Repository). **Modules**: Ingestion Adapters; LLM Extraction; Computer Vision Extraction; External Data Connectors; ETL & Validation Pipeline. |
| Semantic Integration and Reasoning Layer | Instantiation of entities and relations in the Multi-Domain Ontology, causal reasoning, and cross-domain consistency management. | **Components**: Multi-Domain Ontology; Reasoning and Inference Engine. **Services**: Ontology Management API; DB–Ontology Sync Service. |
| Predictive and Decision-Support Layer | Forecasting of operational states, anomaly detection, rule-based validation, and reinsertion of validated predictions. | **Components**: Predictive Model (TGNN). **Modules**: Feature Builder Module; Policy and Rule Check Module. **Services**: Ontology Embeddings Service; Ontology Reinsertion API. |
| Dissemination Interface Layer | Delivery of processed knowledge to users and external systems, interoperability with simulations, and analyst feedback. | **Modules**: COP & Dashboards Module; Reporting & Alerts Module. **Services**: API Gateway (HLA/C2SIM); Feedback & Validation Interface. |

*Ontology Reinsertion API Service* reintroduces validated predictions into the Multi-Domain Ontology, thereby recording provenance metadata, including model version, validation outcome, and confidence scores. This continuous feedback loop maintains semantic coherence across layers and guarantees that newly inferred states immediately enrich the reasoning and dissemination processes within the architecture.

#### 3.4.4. Dissemination and feedback modules and services.

This functional group constitutes the *Dissemination Interface Layer* in Figure 1, delivering processed knowledge to users and external systems while collecting human feedback for continuous refinement. Within this layer, the *COP & Dashboards Module* generates ontology-grounded visualizations, situational summaries, and interactive dashboards that compose the *Common Operational Picture (COP)* across command echelons. The *Reporting & Alerts Module* produces structured reports and alert notifications derived from reasoning and predictive outputs, ensuring timely SA and documentation of key events. Interoperability with modeling, simulation, and C2 environments is provided by the *API Gateway (HLA/C2SIM)*, which translates ontology-grounded updates into standardized messages and ingests external simulation or command events into the semantic core. Finally, the *Feedback & Validation Interface* enables analysts to review, annotate, and validate system outputs; accepted feedback is propagated through the Ontology Management API and, when required, routed back to the ETL & Validation Pipeline for provenance tracking and data correction.

Figure 1 provides a high-level layered view of the proposed architecture and its main data and knowledge flows, while Table 1 summarizes the four functional layers and details their decomposition into components, modules, and services.

### 3.5. Data flow and processing pipeline

Information flows through the architecture as a continuous cycle that connects *functional modules and core components* (Figure 3):

1. *Acquisition and Standardization:* Multi-source data are captured and normalized by the *Data and Preprocessing Layer*.
2. *Semantic Integration:* Standardized data are mapped into ontological entities and relationships, creating a unified operational graph.
3. *Reasoning and Inference:* Core components derive implicit knowledge, enforce consistency, and detect anomalies.
4. *Prediction and Projection:* Hybrid models estimate future operational states or mission outcomes.
5. *Dissemination and Feedback:* Results are distributed to users and simulation components; validated feedback updates the ontology and data repositories.

This iterative loop ensures continuous synchronization between perception and prediction, enabling the system to maintain situational relevance in dynamic environments.

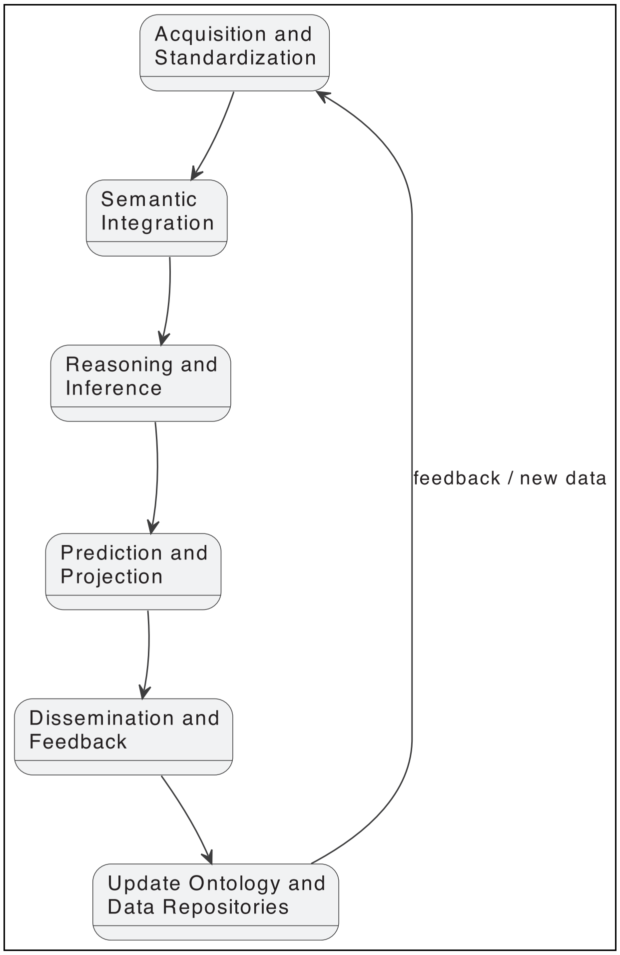


**Figure 3.** Data flow from multi-source acquisition to semantic integration, reasoning, and prediction. Validated projections are reinserted into the ontology and disseminated to dashboards, alerts, and simulation gateways (HLA/C2SIM), with analyst feedback supporting continuous refinement.

### *3.6. Architectural scalability and interoperability*

Scalability is achieved through horizontal decomposition: each *component, module, and service* can be deployed as an independent microservice within a distributed computing environment, supporting load balancing, elasticity, and redundancy. The semantic layer serves as a *lingua franca* among components, enabling incremental evolution without architectural disruption.

Interoperability with simulation federations and decision-support environments is ensured through adherence to open data standards and exchange models such as the IEEE *HLA*[15,16] and NATO's *C2SIM* standard,[18] in addition to spatial data specifications such as GeoSPARQL.[32] These standards provide a formal foundation for federated simulation, automated information exchange, and integration of command-and-control (C2) across heterogeneous systems. They also facilitate interoperability between the proposed architecture and existing M&S environments, ensuring consistency of ontological representations and data models.

This design enables the same ontological backbone to support both operational decision loops and synthetic training environments, fostering dual-use development, conceptual validation, and seamless integration into joint M&S ecosystems.

Taken together, the layered architecture, ontology-centric reasoning, and TGNN-based projection establish a coherent pipeline from perception to prediction. Interoperability via HLA/C2SIM and user-in-the-loop feedback enables both operational decision support and simulation-based validation. This foundation underpins the design choices discussed next and guides the proposed integration and evaluation path.

## 4. Discussion and design rationale

The proposed architecture integrates ontologies, structured databases, and artificial intelligence (AI) components within a unified framework to enhance *SA* and decision support in *MDO*. This section discusses the theoretical motivations for each architectural element and explains how specific design choices address operational, cognitive, and technical challenges identified in section 2.

### *4.1. Rationale for ontology-driven design*

Ontologies constitute the semantic backbone of the system. They provide a formal, machine-interpretable representation of entities, actions, and causal relations across domains, addressing a fundamental limitation of current data-centric architectures: the lack of shared semantics. As Kokar et al.[26] demonstrated, ontology-based SA systems enable explicit reasoning about relationships that remain implicit in purely statistical or rule-based frameworks. By embedding such structures within the architecture, the system achieves semantic coherence, interoperability, and traceability.

From a cognitive perspective, ontologies enable systems to operate more closely in line with human reasoning patterns. They mirror the mental models described by Endsley and Jones,[21] in which comprehension arises from recognizing causal and hierarchical relationships among perceived elements. In a multi-domain context, this capacity is crucial: relationships among the energy, logistics, and command layers are often causal rather than correlative and thus must be represented as logical dependencies. The ontology, therefore, functions as a "semantic map" of the operational environment, providing grounding for both human interpretation and machine reasoning. In architectural terms, these functions are implemented by the *Multi-*

*Domain Ontology*, supported by the *Ontology Management API* and the *DB–Ontology Sync Service* to ensure continuous semantic alignment.

### 4.2. Integration of databases and semantic layers

The use of a structured database complements the ontology by ensuring persistence, query efficiency, and temporal traceability of information. Relational models guarantee data integrity and reproducibility, which are essential for validating situational assessments. Prior work[33] shows that the tight coupling between ontology management frameworks and structured databases facilitates bidirectional synchronization between symbolic knowledge and factual data.

This dual-layer design—syntactic persistence (database) and semantic reasoning (ontology)—enables a dynamic balance between scalability and interpretability. The database handles high-volume ingestion, while the ontology abstracts and integrates meaning. The resulting architecture overcomes the typical fragmentation of domain-specific databases by providing a consistent conceptual framework across all operational dimensions. This interaction is mediated by the *DB–Ontology Sync Service*, which maintains referential integrity between database records and ontology individuals.

### 4.3. Neuro-symbolic integration and predictive modeling

The incorporation of a predictive neural component addresses the limitations of purely rule-based systems in environments with nonlinear interactions and emergent behavior. Recent advances in neuro-symbolic AI show that combining symbolic constraints with learned representations improves both robustness and explainability.[28,29] Within this architecture, embeddings derived from the ontology serve as structured inputs to a *TGNN*, which combines the adaptability of deep learning with the ontology's relational and temporal structure. This hybrid approach allows the system to generalize from observed data while remaining bounded by the semantic rules encoded in the ontology.

Predictive reasoning supports Level 3 SA as defined by Endsley,[20] enabling projection of possible future states of the operational environment. By integrating ontology-derived knowledge, the neural subsystem does not operate as a ''black box'': its predictions are constrained by causal logic and validated against semantic rules, reducing the risk of incoherent or non-interpretable outputs. This addresses one of the main barriers to the adoption of AI in defense decision support—namely, the requirement for transparent and accountable reasoning processes.[34,35] These functions correspond to the *Predictive Model (TGNN)*, the *Ontology Embeddings Service*, and the *Policy and Rule Check Module*, which ensure that learned predictions remain semantically consistent and operationally valid.

### 4.4. Data fusion, heterogeneity, and scalability

MDO generates a vast spectrum of heterogeneous data—from sensor streams and imagery to text reports and cyber telemetry. Traditional fusion architectures struggle to maintain both scalability and semantic coherence under such conditions.[8,22] The proposed architecture mitigates this by introducing a preprocessing layer that standardizes the data and aligns it with ontological schemas before reasoning. This modular design ensures that new data sources can be integrated without altering the core reasoning components, supporting long-term scalability.

The semantic integration layer also enhances system resilience. By establishing explicit relationships between domains, the ontology enables the detection of cascading effects—for example, how disruptions in power networks may affect command infrastructures or cyber operations.[5] This capacity for cross-domain propagation analysis underpins more advanced resilience and convergence assessments, implemented through the *Reasoning and Inference Engine* and the ontology's causal relations.

### 4.5. Explainability and human oversight

Explainability is both a cognitive and operational requirement in defense decision-support systems. Automated recommendations must be traceable and auditable, particularly when influencing command decisions under uncertainty. The architecture ensures explainability at two levels: (1) through ontological reasoning, which provides transparent logic-based justifications, and (2) through the retention of intermediate states within the structured database, enabling post hoc analysis and verification.

This dual-layer transparency enables human operators to interrogate not only what the system concludes but also why it reached that conclusion. All validated predictions are reinserted into the ontology via the *Ontology Reinsertion API Service*, with provenance metadata (model version, confidence, validation outcome) stored in the SQL repository. Such a design aligns with current ethical and regulatory expectations for AI in military contexts, which emphasize accountability and human-in-the-loop supervision.[35]

### 4.6. Interoperability and simulation-based validation

Interoperability represents both a design principle and a validation requirement. By adhering to open standards such as the IEEE *HLA*[16] and NATO's *Command-and-Control Systems—Simulation Systems Interoperation*

*(C2SIM)* Standard,[18] the system can interoperate with existing simulation federations and C2 frameworks.[17] This capability enables the validation of architectural concepts in synthetic environments before operational deployment, thereby reducing risk and improving reproducibility.

Agent-based and federated simulations provide controlled testbeds for assessing the behavior of distributed components under realistic constraints. They can be used to evaluate performance indicators such as data latency, reasoning accuracy, precision/recall of predictive alerts, false-alarm rate, and the proportion of predictions that pass rule-based validation (explainability coverage). Moreover, integration with simulation environments supports *conceptual validation*, an acknowledged practice in which theoretical architectures are validated using representative models rather than full-scale prototypes.[9,17,36]

### 4.7. Architectural implications

Taken together, these design choices contribute to three key outcomes:

1. *Cognitive alignment*. The ontology formalizes shared mental models of the operational environment, enhancing alignment between human decision-makers and machine reasoning.
2. *Semantic interoperability*. The architecture bridges syntactic, structural, and semantic layers, allowing heterogeneous systems to exchange not only data but also meaning.
3. *Scalable explainability*. The integration of databases, ontologies, and neural models creates a pipeline where traceability and predictive power coexist, supporting both operational and analytical decision-making.

These principles collectively support the long-term vision of an adaptive, ontology-enabled decision-support environment for MDO that integrates data, simulation, and human cognition within a unified architectural framework.

### 4.8. Limitations and trade-offs

While beneficial, the proposed approach entails inevitable trade-offs. Ontology curation requires domain expertise and incurs maintenance costs as operational taxonomies evolve. Embeddings may drift from the evolving ontology and require periodic retraining to preserve semantic coherence. Rule-based validation introduces latency and may over-constrain recall in predictive tasks. Finally, synchronization between the *DB–Ontology Sync Service* and the predictive components must be carefully managed to avoid stale or inconsistent states. These limitations motivate the validation and evaluation strategies outlined in subsequent sections and inform directions for future work.

## 5. Integration and validation path

This section outlines a conceptual integration and validation path aligned with the contribution's methodological scope, focusing on architectural coherence and integration readiness rather than empirical performance assessment.

Accordingly, the conceptual nature of the proposed architecture requires a validation strategy that demonstrates its internal consistency, potential for interoperability, and readiness for integration into M&S environments. Rather than pursuing direct operational testing, which would require classified data and large-scale deployment, validation can be achieved through a staged approach that combines agent-based experimentation, federated simulation, and semantic interoperability assessments. This approach follows the principle of *conceptual validation*, widely recognized in the M&S community, which evaluates the plausibility and completeness of a design before its physical implementation.[17]

### 5.1. Progressive validation strategy

The proposed validation path consists of four complementary stages, each addressing a specific architectural dimension: data, semantics, reasoning, and interoperability.

1. *Stage 1—Semantic Coherence and Ontology Testing*. The first step verifies the consistency and logical soundness of the Multi-Domain Ontology. Automated reasoners are used to detect class inconsistencies, redundant relations, and unresolvable property constraints. Unit tests validate that newly introduced entities or metrics during ontology evolution preserve the correctness of reasoning and do not produce logical contradictions. This stage corresponds to the *conceptual verification* of the semantic layer.
2. *Stage 2—Module-Level Verification*. Each core module—the *Data and Preprocessing Layer*, the reasoning engine (*Semantic Integration Layer*), and the predictive component (*Decision-Support Layer*)—is evaluated in isolation using synthetic data sets and controlled simulation inputs. The objective is to confirm that module outputs conform to expected ontological structures and maintain traceability. Techniques from software-in-the-loop validation can be employed to emulate data ingestion, reasoning triggers, and neural predictions.
3. *Stage 3—Integration in Federated Simulation Environments*. The verified modules are integrated

into a distributed simulation federation compliant with the HLA Standard (IEEE 1516.x). In this setting, the ontology-driven reasoning system acts as a federate responsible for semantic synchronization among other federates representing sensors, command centers, and logistic assets. The C2SIM Standard defines message formats for exchanging operational data between the ontology layer and simulation components, ensuring bidirectional semantic interoperability.[9,17] Performance indicators such as event latency, semantic message integrity, and reasoning throughput are recorded to assess scalability and interoperability.[37]

4. *Stage 4—Scenario-Based Conceptual Validation*. The final stage employs agent-based and system dynamics models to represent realistic MDO scenarios. The architecture is instantiated as a semantic middleware that mediates interactions among simulated domains (e.g. cyber–energy–logistics). By monitoring emergent behavior and the propagation of situational updates, researchers can verify that the architecture supports coherent cross-domain reasoning and maintains consistency under dynamic conditions. Such experiments enable comparison of alternative architectural configurations, thereby supporting iterative refinement.

## 5.2. Federation architecture and testbed design

The envisioned validation environment adopts a hybrid federation that combines agent-based models for autonomous decision entities with physics-based or discrete-event models as federates representing infrastructure dynamics and command nodes. Each federate publishes and subscribes to data according to the HLA *Object Model Template (OMT)*, while the ontology-driven core manages semantic harmonization and event correlation across federates. This configuration allows for the assessment of:

- *Semantic interoperability*—verifying that ontological updates propagate correctly to all subscribed federates, avoiding data duplication or loss of meaning.
- *Causal traceability*—confirming that simulated causal chains (e.g. power disruption → communication degradation → command delay) are correctly inferred by the reasoning module.[5]
- *Architectural scalability*—measuring system performance when scaling the number of federates or data streams, using metrics such as event latency and ontology reasoning time.

These metrics provide quantitative evidence of integration readiness while remaining within unclassified, simulation-based settings.

## 5.3. Application domains and use-case examples

Several synthetic use cases can be employed to test the architecture within a federation:

- *Joint Operations Scenario:* Simulation of coordinated air–land–cyber operations, where the ontology integrates mission data and predicts the impact of cyber disruptions on kinetic effects.[12,38]
- *Crisis Management Scenario:* Modeling of cascading failures in civil–military infrastructures (e.g. energy and logistics), validating the system's ability to maintain SA under partial information.[8]
- *C2 Decision-Support Scenario:* Integration with a simulated command environment using C2SIM message formats,[18] testing how semantic reasoning supports course-of-action (COA) assessment and recommendation.[39]

Each scenario can be configured to varying levels of complexity to progressively test the architecture's scalability, interpretability, and responsiveness.

## 5.4. Toward interoperable decision-support ecosystems

Beyond standalone testing, the architecture is designed to serve as a bridge between operational decision-support systems and the broader defense M&S ecosystem. By using shared ontologies and standardized exchange models, data generated during exercises or training federations can be reused directly for analysis, and vice versa. This reciprocal link promotes a virtuous cycle in which simulation informs decision support, and operational data enhance the model's fidelity.[17] The resulting ecosystem supports continuous conceptual validation, allowing architectural refinements to be tested and verified within synthetic environments before field deployment. Through staged semantic verification, modular testing, and simulation-based validation, the system's coherence, scalability, and interoperability can be progressively demonstrated without relying on classified data or full operational trials. This staged validation approach provides a structured roadmap for evolving the ontology-driven architecture from conceptual design to an interoperable prototype aligned with emerging defense standards.

## 6. Conclusion and future work

This paper presents a scalable, ontology-driven architecture designed to enhance SA and decision support in MDO. The proposed framework consolidates semantic reasoning, data management, and predictive analytics within a unified conceptual design that balances explainability, scalability, and interoperability. By integrating ontologies, structured databases, and hybrid neuro-symbolic components, the architecture provides a coherent semantic backbone that supports both operational decision-making and simulation-based validation.

From a theoretical standpoint, the architecture advances the current state of the art in three key directions. First, it defines a *conceptual ontological framework* that unifies the physical, cyber, and cognitive dimensions of MDO, providing the basis for cross-domain reasoning and semantic consistency. Second, it embeds predictive and adaptive components that project future system states while remaining bound by explicit logical constraints. Third, it defines a validation pathway grounded in established M&S standards—specifically, HLA and C2SIM—that allows conceptual verification to precede operational implementation.[17]

The design rationale follows cognitive and operational imperatives identified in the literature. Ontologies ensure shared understanding and traceable reasoning,[26] databases provide reliable data persistence,[33] and AI components introduce adaptive and predictive capabilities.[28,29] Together, these elements establish an architecture that is not only technically coherent but also cognitively aligned with the decision-making processes of commanders operating in complex and uncertain environments.[21,35]

### 6.1. Research and development roadmap

Future work will implement and validate the architecture through a progressive, multi-layered roadmap encompassing four main directions:

1. *Ontology expansion and refinement*. The current conceptual ontology[31] will be extended to cover underrepresented domains, such as space and electromagnetic operations, and to include standardized metric definitions to support quantitative reasoning.[32] Alignment with existing domain ontologies will ensure interoperability with NATO and national frameworks.
2. *Simulation-based validation*. Integration within federated environments will proceed using the HLA standard for runtime coupling and the C2SIM format for semantic data exchange. These testbeds will verify scalability and cross-domain reasoning performance in synthetic yet operationally relevant scenarios.[9,17]
3. *Neuro-symbolic prototyping*. The predictive module will be instantiated as a TGNN constrained by ontology embeddings, following recent work on neuro-symbolic AI.[12,28] Experiments will measure explainability, reasoning coherence, and computational efficiency in high-performance computing (HPC) environments.
4. *Integration into decision-support ecosystems*. Long-term research will explore interoperability between the proposed architecture and existing decision-support and C2 Systems, supporting applications across analytical, operational, and educational contexts. Such integration will promote continuous validation cycles between simulation exercises and real-world decision environments.

### 6.2. Broader implications

Beyond its immediate technological scope, the proposed architecture suggests a potential methodological direction toward *ontology-enabled systems engineering*. Treating semantics as a first-class design principle—rather than as a post hoc integration layer—may help defense information systems improve transparency, adaptability, and resilience in multi-domain contexts. Although further empirical validation is required, this perspective outlines a pathway toward more interoperable, explainable, and cognitively aligned architectures for command, control, and decision-support systems.

### 6.3. Final remarks

The work presented represents an early yet necessary step toward unifying semantic modeling, artificial intelligence, and simulation into a coherent ecosystem for defense decision support. While the architecture remains at a conceptual and architectural maturity level *TRL 1–2*), this choice reflects the paper's focus on conceptual and architectural validation rather than empirical performance. In line with recognized practices in the M&S community, conceptual validation serves as a precursor to implementation, ensuring internal coherence, semantic alignment, and integration readiness before resource-intensive prototyping.[17] The architecture's modularity and adherence to open standards make it suitable for incremental development and cross-institutional experimentation. By enabling progressive validation through simulation federations and promoting explainability through ontological reasoning, the proposed framework contributes to the long-term vision of achieving reliable and interoperable SA in MDOs.

## Acknowledgment

The authors gratefully acknowledge the ''HPC4AI'' initiative[40] for providing access to high-performance computing resources that supported preliminary implementation of this work.


## Authors' note

The study does not involve human participants or animal subjects. All considerations related to the use of artificial intelligence (AI) and machine learning (ML) in defense and security contexts were conducted in accordance with applicable national and international regulations and ethical guidelines.


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## Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

## Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.


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