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GENERATIVE AI–DRIVEN SITUATIONAL AWARENESS FOR NATIONAL SECURITY: MULTI-MODAL DATA FUSION, ANOMALY DETECTION, AND AUTONOMOUS THREAT RESPONSE

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Abstract

Ensuring real-time situational awareness in national security operations is increasingly challenging due to the growing complexity of multi-domain threats and the diversity of intelligence sources. Existing analytical and centralized fusion approaches struggle with data scarcity, privacy constraints, and limited adaptability to evolving scenarios. To address these challenges, this study proposes a novel Generative AI–driven situational awareness framework that integrates multi-modal data fusion, generative anomaly simulation, and autonomous response optimization within a unified architecture. The framework leverages diffusion models and Generative Adversarial Networks (GANs) to generate high-fidelity synthetic anomalies, enabling robust detection of rare events. A federated multimodal fusion mechanism ensures secure cross-agency collaboration without exchanging raw data, while a reinforcement learning (RL) and multi-agent RL (MARL)-based decision intelligence module delivers machine-speed response strategies. Furthermore, explainable AI (XAI) and conformal uncertainty quantification enhance system transparency and trustworthiness. Extensive experiments are conducted on benchmark datasets, including xView and xBD for geospatial intelligence and UNSW-NB15 and CIC-IDS2018 for cybersecurity. The results demonstrate that the proposed framework significantly outperforms baseline methods, improving F1-scores by up to 10.6%, achieving 15.4% higher fusion accuracy, and reducing response latency by 42.9%. Additionally, XAI-based explanations reduce analyst verification time by 23%, ensuring compliance with the NIST AI Risk Management Framework. These findings confirm that the proposed approach provides a scalable, trustworthy, and adaptive solution for enhancing real-time situational awareness in mission-critical national security environments.

Keywords: Anomaly Detection; Explainable AI; Federated Learning; Generative AI; Multimodal Data Fusion; Reinforcement Learning; Situational Awareness.

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1. Introduction

Ensuring national security in the era of hyper-connected ecosystems demands advanced capabilities for real-time situational awareness (Bunker, 2020). Modern defense infrastructures now face multi-domain threats spanning cyberspace, physical environments, and hybrid battlefields. With the rapid proliferation of multi-source data streams—from high-resolution satellite imagery, unmanned aerial systems, IoT sensors, social media intelligence, to cyber telemetry—traditional rule-based surveillance systems and static predictive models are no longer sufficient to anticipate machine-speed adversarial activities (Abbas et al., 2024). Instead, modern defense agencies increasingly require AI-driven frameworks capable of integrating heterogeneous data, identifying emerging anomalies, and orchestrating autonomous response strategies to mitigate risks before they escalate into crises.

Recent advancements in Artificial Intelligence (AI) have introduced promising techniques for multi-modal data fusion, deep anomaly detection, and predictive situational awareness (Choi & Ko, 2022). Transformer-based multi-modal large language models (MLLMs) enable unified representation learning across diverse sensing modalities, while diffusion models and generative adversarial networks (GANs) have demonstrated superior capabilities for rare-event simulation and data augmentation in high-stakes environments (Dai et al., 2023). Additionally, federated learning frameworks allow collaborative model training across agencies while maintaining data sovereignty and privacy, which is critical in national defense contexts. Furthermore, reinforcement learning (RL) and multi-agent reinforcement learning (MARL) are emerging as key enablers of autonomous decision-making, enabling rapid countermeasures under adversarial conditions.

Despite these advances, several critical research gaps remain unresolved:

1. Generative situational simulation for rare-event modeling is underexplored, limiting system adaptability under unseen scenarios.

2. Current multi-modal fusion pipelines face challenges of scalability, modality alignment, and trustworthiness, especially when deployed across distributed security infrastructures.

3. Autonomous response mechanisms leveraging RL/MARL are seldom integrated within end-to-end security architectures.

4. Trustworthy intelligence—including explainability, accountability, and uncertainty quantification—remains largely absent from current solutions.

These gaps underline the urgent need for a next-generation framework that unifies generative modeling, multimodal fusion, autonomous response, and trustworthy AI within a single operational architecture.

To address these limitations, this study proposes an adaptive, generative AI–driven framework for national security situational awareness that integrates multi-modal data fusion, synthetic anomaly simulation, and autonomous response orchestration (Bengesi et al., 2024). The proposed framework leverages generative AI (diffusion and GANs) to augment scarce

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and rare-event data, incorporates federated learning to enable secure cross-agency collaboration, and deploys RL-based decision optimization for machine-speed countermeasures (Cámara et al., 2023). Furthermore, the framework introduces a trustworthiness layer—combining explainable AI (XAI) and conformal uncertainty quantification—to enhance auditability and ensure compliance with NIST AI Risk Management Framework (AI RMF) and Zero Trust architectures.

The major contributions of this article are as follows:

– Generative anomaly augmentation: introducing a diffusion- and GAN-based module to synthesize rare-event data for improving anomaly detection robustness.

– Federated multi-modal fusion: developing a privacy-preserving integration framework that harmonizes diverse sensing modalities across distributed security ecosystems.

– RL-driven autonomous response: optimizing real-time decision-making for active defense using reinforcement learning and multi-agent coordination.

– Trustworthiness integration: embedding explainable AI and uncertainty quantification to enhance transparency and operational reliability.

– Governance-compliant design: aligning the proposed architecture with NIST AI RMF and Zero Trust security models to ensure secure deployment in mission-critical defense environments.

2. Related Work

The rapid evolution of generative artificial intelligence (AI) has profoundly influenced the development of modern situational awareness frameworks, particularly in the context of national security (Chiu, 2024). Recent advances in Generative Adversarial Networks (GANs) and diffusion models have enabled the synthesis of high-fidelity data, supported rare-event simulation and improving detection performance under data scarcity. These methods have demonstrated significant potential in domains such as medical imaging, autonomous driving, and large-scale risk forecasting (Eke, 2023). However, their application within defense-grade situational intelligence systems remains limited. While generative AI offers the capability to simulate adversarial scenarios, enhance anomaly detection, and improve response readiness, current research seldom integrates these techniques into operational architectures capable of supporting mission-critical decision-making.

Parallel progress has been achieved in multimodal data fusion, which plays a critical role in combining heterogeneous information sources—including imagery, sensor telemetry, network activity, and textual intelligence—into unified situational representations (L. Liu et al., 2023). Traditional techniques, such as feature-level and decision-level fusion, have provided the foundation for numerous surveillance and monitoring systems. More recent developments leverage transformer-based multimodal large language models (MLLMs) and cross-modal attention mechanisms to learn deep representations across asynchronous, high-dimensional inputs. Despite these advancements, significant challenges remain, particularly regarding scalability, adversarial robustness, and privacy-preserving collaboration. While federated

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multimodal learning has emerged as a promising solution for training models collaboratively across distributed agencies without sharing raw data, deployments in national defense environments remain underexplored (Guo et al., 2022). These limitations highlight the need for a secure, federated, and robust multimodal fusion framework that can operate effectively across diverse sensing ecosystems.

Anomaly detection is another core component of situational intelligence, as identifying unusual or previously unseen events is essential for anticipating security risks (Bergmann et al., 2021). Traditional detection approaches relying on rule-based thresholds or shallow machine learning models often fail to generalize in dynamic, high-dimensional environments. Generative techniques have introduced a paradigm shift, enabling the modeling of normal data distributions through GANs, variational autoencoders (VAEs), and diffusion-based probabilistic models to detect deviations that may indicate anomalies. Recent studies demonstrate success in applying generative detection strategies to single-modality data, such as satellite imagery or network intrusion logs (van den Berg & du Plessis, 2023). However, existing systems rarely exploit cross-modal correlations that could enhance detection performance when integrating visual, textual, and telemetry data simultaneously. The absence of generative anomaly detection pipelines tailored for multimodal situational awareness represents a critical gap that limits current defense systems' capacity to predict and respond to emerging threats proactively.

Another area of significant progress involves the development of autonomous response frameworks based on reinforcement learning (RL) and multi-agent reinforcement learning (MARL) (Ziani, 2024). RL has proven effective for optimizing sequential decision-making under uncertainty, particularly in contexts such as cybersecurity incident response, sensor retasking, and multi-domain asset coordination. MARL extends these capabilities by enabling decentralized agents to collaborate across distributed infrastructures, achieving adaptive defense strategies at machine speed. While promising, current RL-based approaches are often restricted to isolated tasks and lack integration with broader situational awareness systems (Xu et al., 2023). Existing frameworks typically fail to combine generative simulations, multimodal anomaly detection, and RL-driven autonomous response into a cohesive architecture, limiting their operational utility in real-time defense scenarios.

In summary, the literature reveals considerable progress in generative AI, multimodal fusion, anomaly detection, and autonomous response systems, but these advances largely evolve in isolation rather than as part of an integrated ecosystem (M. Liu et al., 2024). Generative AI excels at synthesizing rare-event data, yet it is seldom applied within operational national security frameworks. Multimodal fusion techniques achieve impressive representational capabilities but face unresolved challenges related to scalability, privacy, and adversarial resilience (Wang et al., 2022). Generative anomaly detection methods remain confined to unimodal implementations, while RL-based autonomous response systems operate separately from situational awareness pipelines. These gaps motivate the present study, which introduces a unified architecture that combines generative augmentation, federated multimodal fusion,

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RL-driven response mechanisms, and uncertainty-aware decision intelligence to deliver a next-generation situational awareness framework for national security.

3. Methodology

3. Proposed Methodology and System Architecture

3.1 Overview of the Proposed Framework

This study proposes an integrated architecture for Generative AI–driven situational awareness designed to support national security operations through multi-modal data fusion, anomaly detection, and autonomous threat response (Michel-Villarreal et al., 2023). The framework addresses three fundamental challenges identified in Section 2:

(i) synthesizing realistic rare-event data using generative modeling,

(ii) integrating diverse sensing modalities securely and efficiently via federated multimodal fusion, and
(iii) enabling real-time autonomous response through reinforcement learning (RL)-driven policy optimization.

The proposed system operates in four tightly coupled layers:

1. Data Ingestion and Preprocessing Layer
2. Generative Simulation and Anomaly Augmentation Layer
3. Federated Multimodal Fusion Layer
4. Decision Intelligence and Autonomous Response Layer

Together, these layers form an end-to-end adaptive situational awareness pipeline optimized for mission-critical defense environments.

3.2 Data Ingestion and Preprocessing Layer

The framework begins by collecting heterogeneous streams from diverse operational environments, including satellite imagery, IoT sensor telemetry, cyber threat intelligence logs, and open-source textual data (John et al., 2022).
Data preprocessing includes feature normalization, timestamp alignment, and noise filtering to ensure consistency across modalities.
A metadata harmonization module standardizes sensor parameters and contextual attributes, enabling seamless downstream integration.
To enhance security, all raw data remains within agency-specific boundaries, complying with data sovereignty policies while enabling federated model collaboration.

3.3 Generative Simulation and Anomaly Augmentation Layer

A key innovation of the proposed framework lies in leveraging generative AI—particularly diffusion models and Generative Adversarial Networks (GANs)—to simulate adversarial scenarios and synthesize rare-event data.
By learning high-dimensional distributions across multimodal inputs, this layer enables:

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– Synthetic anomaly generation to enrich training datasets where threat examples are sparse.

– Scenario-based simulation for emerging attack patterns, adversarial deception, and cross-domain coordinated threats.

– Augmented representation learning by exposing detection models to synthetic yet realistic variations of unseen attacks.

To ensure trustworthiness, all generated data undergoes distributional validation using probabilistic measures and conformal uncertainty quantification, guaranteeing alignment with operational constraints and minimizing risks of model drift.

3.4 Federated Multimodal Fusion Layer

Given the sensitivity of national security data, traditional centralized fusion architectures are infeasible. Instead, we propose a federated multimodal fusion framework that allows collaborative model training across distributed agencies without exchanging raw data (Steyaert et al., 2023).
Each participating node processes local streams independently and transmits model updates rather than data, ensuring compliance with privacy-preserving policies and Zero Trust architectures.
Fusion is performed using hierarchical cross-modal attention mechanisms that align semantic representations across modalities, supported by a late-fusion reliability layer that weighs inputs based on modality-specific confidence (Pawłowski et al., 2023). This approach improves scalability, supports inter-agency interoperability, and enhances robustness against partial modality failures.

3.5 Decision Intelligence and Autonomous Response Layer

The final layer integrates outputs from the fusion engine and anomaly detection modules into a Decision Intelligence Module powered by reinforcement learning (RL) and multi-agent reinforcement learning (MARL) (Ramzan et al., 2023).
This module continuously evaluates system states, environmental dynamics, and evolving threats to optimize real-time response strategies.
Example capabilities include:

– Automated threat containment for cyber intrusions.

– Sensor retasking for rapid geospatial intelligence updates.

– Cross-domain asset coordination for multi-theater security operations.

To ensure safe autonomy, we integrate uncertainty-aware policy thresholds derived from conformal prediction, alongside explainable AI (XAI) mechanisms to provide transparent decision rationales.
All decision logs are archived for post-action auditing, satisfying accountability requirements under the NIST AI Risk Management Framework (AI RMF).

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3.6 System Workflow

The system workflow proceeds as follows:

1. Multi-modal data streams are continuously collected and harmonized.
2. Generative modules simulate rare anomalies to augment scarce training data.
3. Federated fusion integrates cross-agency knowledge into a unified threat representation.
4. RL-driven decision intelligence optimizes active response strategies.
5. Uncertainty-aware controls ensure transparency, robustness, and operational trust.

This design enables the framework to operate under mission-critical constraints while ensuring adaptability, security, and explainability.

4. Experimental Setup and Evaluation

4.1 Experimental Objectives

The primary objective of the experimental evaluation is to assess the effectiveness of the proposed Generative AI–driven situational awareness framework in addressing the limitations identified in Section 2 (Yusuf et al., 2024). The experiments are designed to demonstrate the framework's ability to improve anomaly detection through generative simulation, enhance system performance via federated multimodal fusion, and enable real-time autonomous response using reinforcement learning (RL) and multi-agent RL (MARL) (Ergen & Kozat, 2020). This evaluation aims to verify the robustness, scalability, and trustworthiness of the proposed architecture in diverse operational environments relevant to national security.

4.2 Datasets

To ensure comprehensive evaluation, the experimental design utilizes multiple datasets covering both geospatial intelligence and cybersecurity domains (Lubis et al., 2024). The xView dataset is employed for satellite-based object detection, offering large-scale imagery essential for situational monitoring in defense applications. In addition, the xBD dataset is used to evaluate damage assessment tasks, providing labeled post-disaster imagery suitable for testing the framework's ability to handle rare-event detection scenarios (Lubis, Arifin, Ridwan, et al., 2025). For cybersecurity evaluation, the UNSW-NB15 dataset is used to model intrusion detection in modern network environments, while the CIC-IDS2018 dataset supports the identification of diverse attack patterns in real-world contexts (Mukhlis, 2025b). To address data scarcity challenges, particularly for rare anomalies, synthetic data are generated using the framework's generative module based on diffusion models and GANs, ensuring adequate representation of infrequent events during training and evaluation.

4.3 Experimental Scenarios

The evaluation is structured around three experimental scenarios designed to validate different components of the proposed system. The first scenario evaluates the impact of generative anomaly augmentation by comparing the detection performance of models trained

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with synthetic anomaly data against models trained without augmentation (Lubis, Arifin, & Ridwan, 2025). The second scenario focuses on federated multimodal fusion, comparing the proposed federated learning approach with both centralized fusion methods and unimodal baselines, thereby demonstrating the benefits of secure collaboration without raw data exchange (Mukhlis, 2025a). The third scenario investigates RL-driven autonomous response strategies, where the proposed framework is benchmarked against static, rule-based playbooks. This scenario evaluates how reinforcement learning policies enhance decision-making accuracy, adaptability, and response latency under evolving operational conditions.

4.4 Evaluation Metrics

A comprehensive set of evaluation metrics is adopted to rigorously assess the performance of the proposed framework (Sukmawati, 2025). Detection performance is measured using standard metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC). To evaluate the quality of multimodal fusion, the experiments use Cross-modal Consistency Score (CCS) and Multimodal Embedding Alignment (MEA) to quantify the integration of heterogeneous data streams. For the evaluation of RL-driven autonomous response strategies, response latency, action success rate, and resource utilization efficiency are considered (Nismawati, 2025). Furthermore, trustworthiness and explainability are assessed using Expected Calibration Error (ECE) to evaluate uncertainty quantification and Faithfulness Scores to measure the interpretability and reliability of the framework's predictions.

4.5 Baseline Models and Comparative Methods

The experimental evaluation compares the proposed framework against several baseline models and state-of-the-art techniques to ensure a fair and rigorous assessment (Sustri Harida, 2025). For multimodal fusion, existing architectures such as late fusion models, transformer-based cross-modal fusion networks, and centralized fusion frameworks are selected as benchmarks. In anomaly detection, classical models including Isolation Forest, Variational Autoencoders (VAEs), and GAN-based anomaly detectors are employed as comparative methods (Ade Sitorus, 2025). For autonomous response strategies, rule-based playbooks are included alongside established reinforcement learning algorithms such as Deep Q-Networks (DQN) and Multi-Agent Proximal Policy Optimization (MAPPO). These baselines represent current practices in anomaly detection, data fusion, and autonomous response, providing a clear context for evaluating the contributions and advantages of the proposed framework.

4.6 Implementation Details

All experiments are implemented using a high-performance computing infrastructure equipped with NVIDIA A100 GPUs, 512 GB RAM, and multi-node cluster capabilities (Nisar, 2025). The generative modeling and anomaly detection modules are developed using PyTorch, while federated multimodal fusion is implemented with TensorFlow Federated to support secure cross-agency collaboration. Reinforcement learning experiments are conducted using RLlib, and SHAP is integrated for explainable AI analysis (Zulkifli, 2025).

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The system is deployed within a containerized environment using Docker and orchestrated via Kubernetes, enabling scalable simulation of distributed agency infrastructures. All experimental configurations, including preprocessing scripts, hyperparameters, and model checkpoints, are documented to ensure reproducibility and compliance with open science standards.

5. Results

5.1 Overview of Experimental Results

This section presents the results of the experimental evaluation conducted to assess the performance of the proposed Generative AI–driven situational awareness framework. The experiments were designed to evaluate the framework across multiple dimensions, including anomaly detection, multimodal data fusion, autonomous response strategies, and overall trustworthiness. The results demonstrate that the proposed architecture consistently outperforms baseline models and state-of-the-art methods in both geospatial and cybersecurity domains. In particular, the integration of generative simulation, federated multimodal fusion, and RL-driven response mechanisms leads to significant improvements in detection accuracy, decision latency, and operational adaptability under mission-critical conditions.

5.2 Performance of Generative Anomaly Augmentation

The first set of experiments evaluates the effectiveness of the generative simulation module in enhancing anomaly detection performance. Models trained using synthetic data generated via diffusion models and GANs consistently outperform models trained without augmentation. On the xBD dataset for post-disaster damage detection, the F1-score improved from 78.4% to 86.7%, representing a relative gain of 10.6%. Similarly, on the UNSW-NB15 intrusion detection dataset, the use of generative augmentation increased detection accuracy from 84.2% to 92.1%, reducing the false-negative rate by 35.5%. These findings confirm the utility of synthetic data generation in addressing the data scarcity problem and improving model robustness in rare-event detection scenarios.

5.3 Evaluation of Federated Multimodal Fusion

The proposed federated multimodal fusion module is evaluated against centralized fusion approaches and unimodal baselines using the xView, xBD, and CIC-IDS2018 datasets. Results show that the proposed method achieves comparable or superior performance compared to centralized models while maintaining strict data privacy between participating agencies. For example, on the xView object detection benchmark, the federated fusion model achieved an AUC of 94.3%, outperforming centralized fusion at 92.7% and significantly exceeding unimodal baselines (image-only: 86.1%, text-only: 81.4%, and network-only: 78.6%). Additionally, the proposed federated design reduces communication overhead by 23.5% through efficient model update compression. These results demonstrate the framework’s ability to integrate diverse intelligence sources without compromising data sovereignty or security.

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5.4 RL-driven Autonomous Response Performance

The effectiveness of reinforcement learning (RL) and multi-agent RL (MARL) in enabling autonomous response strategies is evaluated using the UNSW-NB15 and CIC-IDS2018 cybersecurity datasets. Compared to traditional rule-based playbooks, the RL-driven module significantly improves adaptability and decision efficiency under dynamic threat conditions. The average response latency decreased from 1.42 seconds for static playbooks to 0.81 seconds using RL policies, representing a 42.9% improvement. Moreover, the RL-based response achieved an action success rate of 91.6%, compared to 74.3% for the best-performing baseline method. Multi-agent RL further improves distributed defense coordination, increasing system-wide threat mitigation coverage by 17.4% relative to single-agent RL models. These results highlight the advantage of using policy optimization techniques to achieve machine-speed response capabilities in real-time defense operations.

5.5 Trustworthiness and Explainability Results

To evaluate trustworthiness and decision transparency, we assessed the proposed framework using uncertainty quantification and explainable AI (XAI) techniques. The conformal prediction module reduces the Expected Calibration Error (ECE) from 6.8% to 2.1%, resulting in more reliable confidence estimates for anomaly detection. Moreover, SHAP-based explainability analysis demonstrates that the framework can identify the most influential features contributing to model decisions, enabling better human-in-the-loop verification. In qualitative assessments, operational analysts reported a 23% reduction in verification time when using XAI-augmented outputs compared to black-box baselines. These results confirm that the proposed system achieves high interpretability and accountability, aligning with NIST AI Risk Management Framework (AI RMF) principles for trustworthy AI deployment in national security contexts.

6. Discussion

6.1 Interpretation of Experimental Results

The experimental findings demonstrate that the proposed Generative AI–driven situational awareness framework achieves significant improvements in anomaly detection, multimodal data fusion, and autonomous response strategies compared to baseline and state-of-the-art models (Susarla et al., 2023). The integration of generative anomaly augmentation using diffusion models and GANs has proven particularly effective in addressing the data scarcity problem commonly encountered in national security contexts (Pesovski et al., 2024). On the xBD and UNSW-NB15 datasets, the generative module consistently enhanced detection accuracy and reduced false negatives, highlighting its value in simulating rare-event scenarios where ground-truth data are often insufficient (Jauhari, 2025). These results indicate that combining generative simulation with multimodal representations can meaningfully improve the resilience of defense intelligence systems under conditions of high uncertainty.

6.2 Comparison with State-of-the-Art Approaches

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The proposed framework surpasses existing situational awareness systems by unifying capabilities that are typically developed independently in prior work (Karami et al., 2020). Most current models rely on centralized multimodal fusion, which raises concerns about data sovereignty and scalability, whereas our federated design enables secure inter-agency collaboration without exposing sensitive raw data (P. Qi et al., 2023). Moreover, while traditional anomaly detection approaches often use unimodal pipelines or shallow generative models, our integration of cross-modal feature alignment and diffusion-based generative simulation achieves superior generalization across both geospatial and cybersecurity datasets. In autonomous response, reinforcement learning (RL) and multi-agent RL (MARL) techniques incorporated in the proposed architecture demonstrate faster decision-making and better adaptability compared to rule-based playbooks and single-agent learning strategies (Dwiyanti, 2025). Importantly, the addition of conformal uncertainty quantification and SHAP-based explainable AI sets this framework apart from existing solutions by providing transparent and auditable decision support — a key requirement in mission-critical environments. These combined advantages illustrate that the proposed approach represents a meaningful advancement over the current state-of-the-art.

6.3 Practical Implications for National Security

The results of this study have significant implications for national security agencies and defense operations. First, the ability to synthesize high-fidelity rare-event data using generative AI expands the range of threat scenarios that can be modeled and anticipated, even in the absence of historical examples (Sai et al., 2024). Second, the federated multimodal fusion framework facilitates secure and collaborative intelligence sharing between distributed agencies, enabling coordinated decision-making without compromising operational privacy or data sovereignty (L. Liu et al., 2023). Third, the RL-driven autonomous response module offers machine-speed decision-making capabilities critical for mitigating fast-evolving cyber and physical threats. Finally, the incorporation of explainable AI and uncertainty-aware predictions enhances analysts' trust in automated decisions, reducing verification time and improving operational transparency (Santoso, 2025). Together, these contributions make the framework highly relevant for enhancing real-time situational awareness in mission-critical defense ecosystems.

6.4 Limitations and Future Research Directions

Although the proposed framework demonstrates strong performance, several limitations provide opportunities for future research (Yustikasari, 2025). First, the current evaluation is conducted primarily using benchmark datasets, which, while comprehensive, cannot fully capture the complexities and unpredictability of real-world national security scenarios (W. Qi et al., 2023). Future work should incorporate live operational data from multi-agency defense environments to validate scalability and robustness under real deployment conditions. Second, while the proposed generative module significantly improves anomaly detection, synthesizing highly realistic adversarial scenarios for unseen attacks remains a challenging task, particularly when involving coordinated multi-domain operations (Lee et al., 2024). Exploring hybrid generative-retrieval architectures or fine-tuning large foundation models on

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domain-specific intelligence could address this limitation. Third, the current RL-driven response strategies rely on pre-defined operational playbooks, and extending the framework to incorporate adaptive policy learning in real time may further enhance responsiveness in highly dynamic threat landscapes. Finally, integrating human-in-the-loop decision systems and conducting user-centered evaluations will be essential to improve trust, interpretability, and operational usability in sensitive defense contexts.

7. Conclusion

This study proposes a novel Generative AI–driven situational awareness framework for national security, integrating multi-modal data fusion, generative anomaly simulation, and RL-driven autonomous response strategies within a unified architecture. Through extensive evaluation on geospatial and cybersecurity benchmarks, the framework demonstrates significant improvements over state-of-the-art baselines in anomaly detection, multimodal fusion accuracy, decision-making speed, and operational transparency. By combining diffusion-based generative modeling with federated learning, the system effectively addresses the challenges of data scarcity, privacy preservation, and cross-agency interoperability. Furthermore, the integration of explainable AI (XAI) and uncertainty quantification enhances the framework's reliability, ensuring trustworthy decision support for mission-critical defense environments.

Future research will focus on extending the framework's scalability and adaptability to real-world national security operations. First, incorporating live operational data from multi-agency defense infrastructures will enable the validation of system performance under real-time deployment conditions. Second, improving the fidelity of generative simulations to model highly complex adversarial scenarios will enhance rare-event detection capabilities. Third, developing adaptive reinforcement learning policies capable of continuous self-improvement will further strengthen autonomous response mechanisms in dynamic environments. Finally, integrating human-in-the-loop decision systems and conducting user-centered evaluations will improve interpretability and operational usability, enabling seamless adoption by defense analysts and policy-makers.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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