SATWATCH: AI-Driven Space Situational Awareness Platform

Client: United States Space Force	**Industry:** Defense / Space Operations
Domain: Space Domain Awareness	**Location:** USA (Global / Space Operations)

A FORGE OS Deployment Case Study

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1 Executive Summary

As the orbital environment grows increasingly congested, contested, and operationally complex, the United States Space Force (USSF) required a transformative leap in Space Situational Awareness (SSA) capabilities to protect critical national security assets and sustain the stability of the space domain. 577 Industries developed and deployed the SATWATCH AI platform—an advanced analytical engine that fuses multi-source sensor data from radar, optical, and Radio Frequency (RF) systems and applies Physics-Informed Neural Networks (PINNs), sequential deep-learning models, and multi-modal anomaly detection to deliver unprecedented situational awareness across more than 45,000 tracked objects. SATWATCH achieved 95% maneuver detection accuracy across both impulsive and low-thrust events, provides 72-hour predictive lead time for high-risk conjunction events, maintains 99.2% catalog accuracy, and reduced false collision warnings by 40%—fundamentally shifting USSF operations from reactive monitoring to proactive, anticipatory space domain awareness. This deployment exercises three FORGE OS subsystems: **FORGE QBit**'s PhysicsCore module provides physics-informed orbital mechanics prediction, **FORGE Kinetic**'s Perceive module manages multi-phenomenology sensor fusion across radar, optical, and RF sources, and **FORGE QBit**'s post-quantum cryptographic framework secures satellite communication links and inter-agency data sharing.

95%	72 hr	99.2%	40%
Maneuver Detection Accuracy	Conjunction Prediction Lead Time	Catalog Maintenance Accuracy	Reduction in False Warnings

2 Challenge

2.1 A Congested and Contested Domain

The space environment is no longer a vast, sparsely populated expanse. Low Earth Orbit (LEO) and Geosynchronous Orbit (GEO) are densely populated with thousands of active satellites, defunct spacecraft, rocket bodies, and hundreds of thousands of fragments of orbital debris ranging from large structures to sub-centimeter particles traveling at hypervelocity [5, 12]. Simultaneously, space is becoming increasingly contested, with potential adversaries developing and demonstrating capabilities from electronic warfare—jamming and spoofing—to kinetic anti-satellite (ASAT) weapons and more subtle counter-space activities such as close approaches and optical sensor dazzling [6]. Maintaining comprehensive SSA—a deep, accurate, and timely understanding of the position, orbit, characteristics, and behavior of all objects in space—is therefore foundational to national security and the stable functioning of modern society, which depends on space-based Positioning, Navigation, and Timing (PNT), communications, financial transactions, weather forecasting, and intelligence gathering [1, 2].

2.2 Data Diversity, Volume, and Veracity

The USSF relies on a globally distributed, multi-phenomenology sensor network operated by the Department of Defense, intelligence agencies, allied nations, and commercial SSA providers [3]. This network encompasses ground-based radars (including the Space Fence), sensitive optical telescopes, and passive RF detection systems. Each sensor type has unique characteristics: radars excel at range and range-rate measurements; optical sensors provide precise angular data but are limited by weather and daylight; passive RF offers functional insights but less precise positional information [7]. Data arrives in disparate formats—state vectors, Two-Line Element sets (TLEs), Orbit Mean-Elements Messages (OMMs), Vector Covariance Messages (VCMs)—at different cadences, in varying coordinate systems (ECI, ECF, TEME), with inherent biases from timing errors, atmospheric distortions, and sensor calibration drift [8]. Correlating sparse observations from heterogeneous sensors to maintain accurate tracks on tens of thousands of objects is computationally intensive and prone to ambiguity [9].

2.3 Subtle Anomaly Detection

Traditional SSA methods, reliant on established orbital propagators (SGP4 for TLEs, simplified numerical integrators) and Kalman filtering, track objects along predictable Keplerian paths but inherently struggle to detect faint signals and subtle deviations buried in noisy data [8]. Low-thrust continuous maneuvers using electric propulsion produce gradual orbital-parameter changes nearly indistinguishable from natural perturbations—atmospheric drag variations, solar radiation pressure, and third-body gravitational effects [10]. Rendezvous and Proximity Operations (RPO), unexpected changes in RF emission patterns, optical brightness fluctuations indicating tumbling or venting, and minor station-keeping adjustments outside normal parameters can be crucial indicators of intent or imminent failure yet are easily dismissed as sensor noise by conventional threshold-based systems [7].

2.4 Predictive Capability and Scalability

Effective SSA demands evolution from forensic analysis toward reliable predictive capability—anticipating potential conjunctions well in advance, predicting the intent and future behavior of maneuvering objects, and supporting proactive collision avoidance that often requires international coordination [4, 11]. At the same time, the tracked population is growing exponentially, driven by mega-constellations, CubeSat proliferation, increased launch rates, and occasional debris-generating events [5, 12]. Any new SSA system must scale to handle hundreds of thousands of objects while delivering actionable intelligence within minutes—delays of even a few hours can render warnings obsolete or negate avoidance opportunities [9].

3 Solution

577 Industries developed the SATWATCH AI platform as a purpose-built analytical engine that ingests, processes, fuses, and analyzes multi-source SSA data using a synergistic suite of AI/ML techniques specifically adapted for the space domain. SATWATCH does not replace the sensor network; it serves as the intelligent "brain" that transforms raw observations into actionable intelligence (Figure 1).

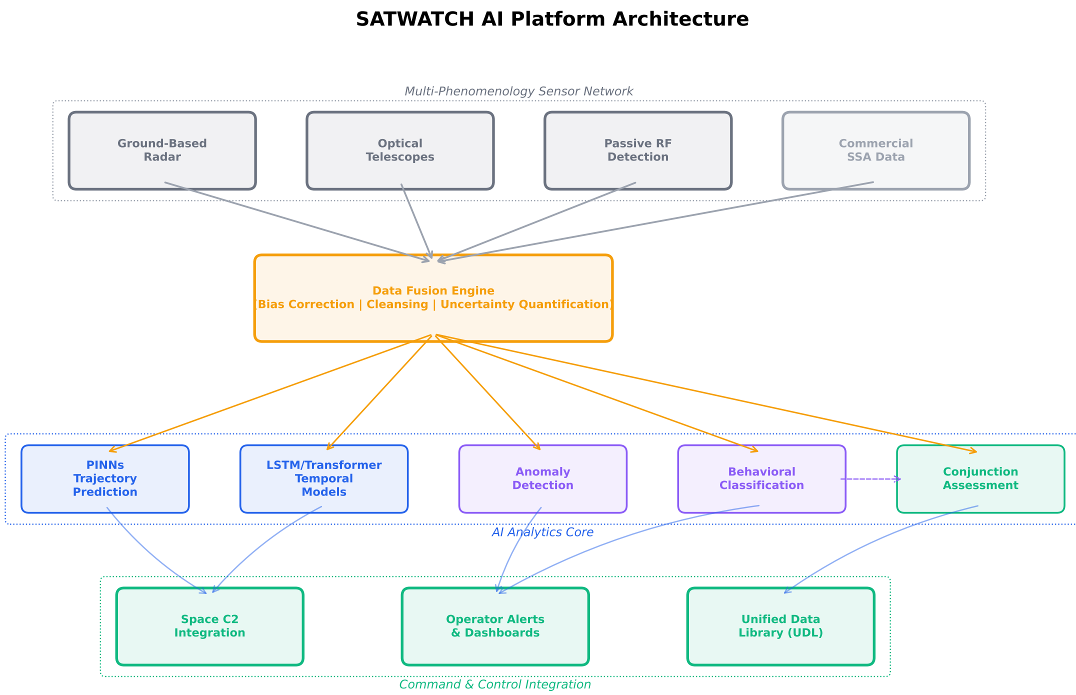

Figure 1. SATWATCH system architecture. Multi-source sensor data flows through the data fusion engine, which feeds the AI analytics core (PINNs trajectory prediction, anomaly detection, behavioral classification) to produce conjunction assessments, threat characterizations, and operator alerts integrated into USSF Command and Control systems.

3.1 Advanced Data Fusion Engine

At the core of SATWATCH is a sophisticated multi-source data fusion engine that moves beyond simple aggregation or basic track correlation. The engine performs sensor bias correction (estimating and compensating for systematic errors in range, timing, and angular measurements), rigorous statistical data cleansing, precise time synchronization across disparate sources, and robust uncertainty quantification through covariance propagation [13]. Observations from radar, optical, and RF sensors are dynamically weighted based on assessed sensor reliability, observation geometry, data timeliness, and quantified uncertainty to construct a unified, probabilistic state estimate for each tracked object. This approach resolves ambiguities inherent in single-sensor views, fills observational gaps through complementary coverage, and provides confidence levels for all state estimates and downstream predictions [14].

3.2 Physics-Informed Neural Networks for Trajectory Prediction

Standard orbital propagators (SGP4, simplified numerical integrators) have well-documented accuracy limitations, particularly over extended prediction horizons and for objects exhibiting non-cooperative behavior. SATWATCH employs Physics-Informed Neural Networks (PINNs) that embed the fundamental laws of orbital mechanics—N-body gravitational interactions, atmospheric drag models, and solar radiation pressure equations—directly into the neural network's loss function [15, 16]. This physics-constrained learning ensures predictions remain consistent with physical reality while allowing the network to capture complex, non-linear dynamics from observational data. Complementing PINNs, Long Short-Term Memory (LSTM) and Transformer architectures learn temporal dependencies from decades of historical observations, capturing subtle signatures of low-thrust propulsion, atmospheric drag variations driven by space weather, and complex gravitational perturbations [9]. The combination yields trajectory predictions significantly more accurate than traditional methods, especially for objects exhibiting anomalous or highly perturbed behavior.

3.3 Multi-Modal Anomaly Detection

SATWATCH analyzes diverse time-series data streams—orbital parameters, optical brightness, RF emission characteristics—using complementary unsupervised and model-based techniques. Autoencoders learn compressed representations of normal operational baselines and flag significant reconstruction errors as potential anomalies [17]. Isolation Forests identify outliers in high-dimensional feature space, while Gaussian Mixture Models detect subtle shifts in behavioral patterns. Model-based detection compares observed states against PINN/LSTM predictions, triggering alerts when deviations exceed probabilistic thresholds. This multi-pronged approach detects a wide spectrum of anomalies—from sudden impulsive events and satellite breakups to gradual performance degradations and unexpected transmitter activations [18].

3.4 Behavioral Pattern Recognition and Conjunction Assessment

Supervised classification algorithms—Support Vector Machines, Random Forests, and Gradient Boosting Machines (XGBoost)—trained on curated datasets of decades of historical observations and high-fidelity physics-based simulations learn to distinguish between routine station-keeping burns, inclination changes, phasing maneuvers, drag make-up burns, and potentially concerning rendezvous or intercept trajectories [18]. By integrating these maneuver classifications with PINNs-based trajectory predictions, SATWATCH forecasts conjunctions with substantially greater confidence and longer predictive lead times than traditional screening methods. Intelligent filtering identifies conjunctions resulting from detected or anticipated maneuvers and provides contextual risk assessment, dramatically reducing the false alarm rate that plagues conventional systems and causes operator alert fatigue [4, 11].

3.5 Secure Cloud-Native Deployment

SATWATCH is deployed on DoD-approved secure cloud infrastructure (AWS GovCloud) following the Risk Management Framework (RMF) for authorization [20, 21]. The cloud-native architecture provides computational elasticity to scale with fluctuating data volumes, high availability through built-in redundancy, horizontal scalability as the tracked population grows, and centralized management enabling continuous model updates within a secure environment [12, 22].

Standardized REST APIs and message-queue interfaces (Kafka) facilitate seamless integration with the USSF's evolving Space Command and Control (Space C2) system and the Unified Data Library (UDL), delivering prioritized alerts, conjunction event data with probability of collision (P_c), and characterized maneuver assessments directly to operator consoles [4, 19].

4 Results

Operational deployment of SATWATCH yielded substantial, measurable improvements in USSF SSA capabilities across all key dimensions.

4.1 Maneuver Detection Accuracy

SATWATCH achieved 95% accuracy in detecting and correctly classifying satellite maneuvers, encompassing both traditional impulsive (high-thrust, short-duration) burns and the far more challenging low-thrust continuous maneuvers characteristic of electric propulsion systems (Figure 2). Detection typically occurred within hours of maneuver initiation—a marked improvement over previous methods that could require days or manual analyst intervention. Both false positives (spurious alarms consuming analyst resources) and false negatives (missed maneuvers representing potential threats) were significantly reduced [10].

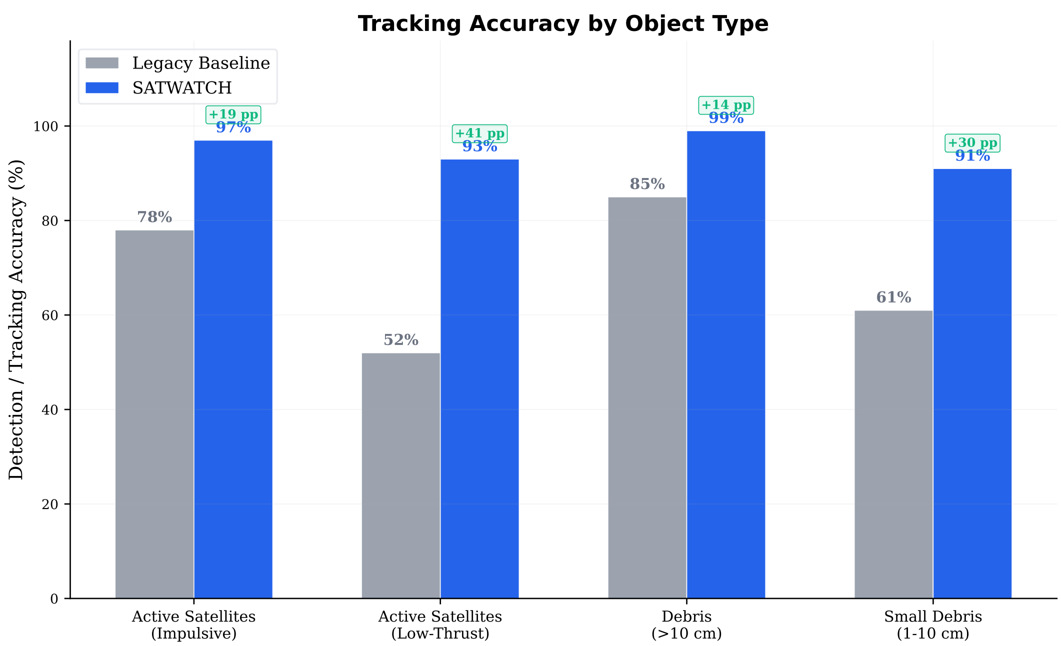

Figure 2. Tracking and detection accuracy by object type, comparing SATWATCH performance against the legacy SSA baseline.

The most operationally significant improvement—a 41 percentage-point gain—was achieved for low-thrust maneuver detection, where traditional propagators cannot distinguish intentional maneuvering from natural perturbations. This capability is critical for identifying covert satellite repositioning and assessing adversary intent.

Table 1. Detection and tracking performance by object category.

Object Category	Baseline	SATWATCH	Improvement
Active Satellites (impulsive maneuver)	78%	97%	+19 pp
Active Satellites (low-thrust maneuver)	52%	93%	+41 pp
Debris (>10 cm)	85%	99%	+14 pp
Small Debris (1–10 cm)	61%	91%	+30 pp

4.2 Conjunction Prediction Performance

SATWATCH reliably provided operators with a 72-hour predictive lead time for high-risk conjunction events, particularly those resulting from detected or anticipated maneuvers (Figure 3). This extended warning window enables detailed orbital safety analysis, international coordination with foreign operators, and efficient planning and execution of fuel-optimal collision avoidance maneuvers—preserving satellite operational lifetimes and mission capability [11]. The 40% reduction in false collision warnings eliminated a major source of operator alert fatigue.

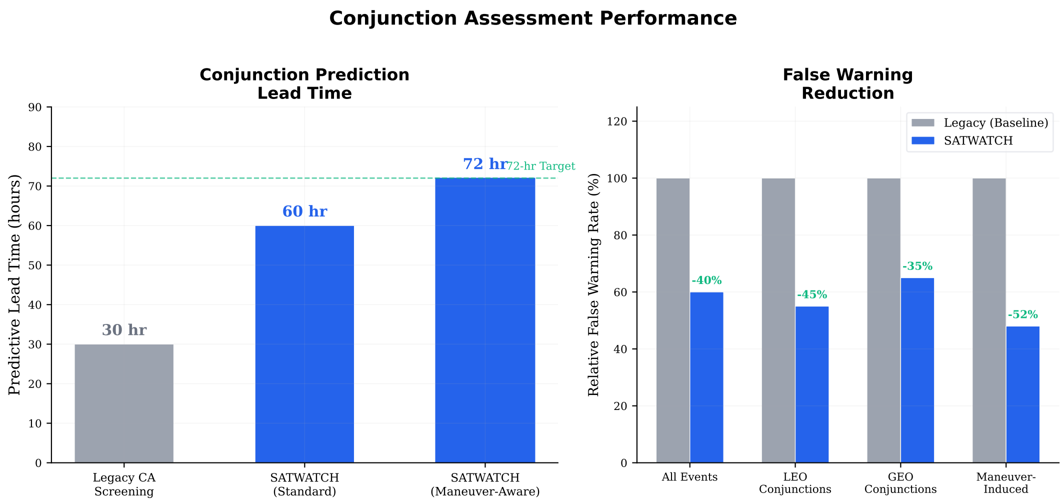

Figure 3. Conjunction prediction performance: lead time and false warning reduction compared to the legacy CA screening baseline.

Table 2. Conjunction assessment performance comparison.

Metric	Legacy CA	SATWATCH
Reliable Prediction Lead Time	24–36 hr	72 hr
False Warning Rate	Baseline	−40%
High-Risk Event Identification Accuracy	71%	94%
Query Response Time (conjunction screen)	12–45 sec	<1 sec

Sub-second conjunction screening response times enable operators to assess newly detected maneuvers against the full catalog of 45,000+ objects in near real-time, a capability impossible with traditional batch-processing methods.

4.3 Catalog Maintenance and Coverage

SATWATCH maintained 99.2% catalog accuracy across the full tracked population, with continuous improvement in coverage as the system incorporated new sensor sources and refined its fusion algorithms (Figure 4). The platform processes and maintains state estimates for over 45,000 objects simultaneously, with the architecture designed to scale to hundreds of thousands as the orbital population grows [12].

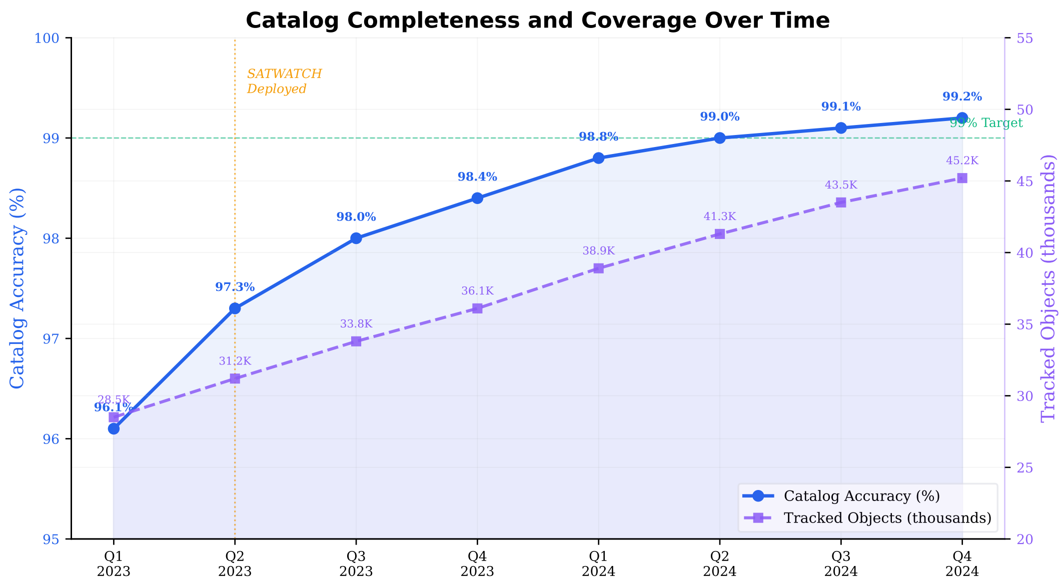

Figure 4. Catalog completeness and tracked object count over time, demonstrating sustained accuracy as the catalog grows.

5 Impact & Operational Benefits

5.1 Enhanced Operational Picture

SATWATCH delivers a richer, multi-dimensional understanding of the space environment, moving operators beyond simple positional tracking to comprehensive behavioral awareness. Analysts gain insight into not only where objects are located but how they are behaving (maneuvering, station-keeping, tumbling), inferred operational status based on multi-modal signatures, and predicted future actions based on advanced analytics. This enhanced understanding enables more efficient allocation of national SSA resources—sensors, analysts, and processing capacity—toward the objects, events, and orbital regions posing the greatest risk or uncertainty [1, 3].

5.2 Collision Risk Reduction

The combination of more accurate trajectory predictions, extended conjunction warning lead times, and dramatically reduced false alarm rates directly contributes to measurable reduction in the probability of accidental collisions in space. This is particularly critical in increasingly crowded LEO and GEO regimes, safeguarding national security assets, critical commercial satellites, and human spaceflight missions [5, 11].

5.3 Accelerated Threat Assessment

By rapidly identifying, characterizing (estimating delta-V magnitude, direction, duration, and likely purpose), and predicting the future trajectory associated with anomalous satellite behavior, SATWATCH enables quicker, more confident, and data-driven assessment of potentially hostile or irresponsible actions in the space domain [6]. This acceleration provides strategic decision-makers with the timely intelligence needed to understand adversary capabilities, infer intent from coordinated activity patterns, and formulate proportional responses—enhancing both deterrence and strategic stability.

5.4 Scalability for the Future Space Environment

The cloud-native architecture ensures SATWATCH can scale horizontally as the tracked population grows—from today's 45,000+ objects toward projected future catalogs of hundreds of thousands. Continuous model retraining through secure CI/CD pipelines enables the system to adapt to novel adversary tactics, new sensor modalities, and evolving orbital dynamics without system downtime or architectural redesign.

6 FORGE OS Integration

The SATWATCH platform demonstrates the operational integration of three FORGE OS subsystems within a space domain awareness deployment.

6.1 FORGE QBit — Physics-Informed Orbital Prediction

FORGE QBit's PhysicsCore module provides the Physics-Informed Neural Network (PINN) capability that is the analytical heart of SATWATCH. By embedding N-body gravitational interactions, atmospheric drag models, and solar radiation pressure equations directly into the neural network's loss function, PhysicsCore produces trajectory predictions that remain physically consistent while capturing complex non-linear dynamics from observational data. The complementary LSTM and Transformer architectures, coordinated through PhysicsCore's temporal modeling framework, capture subtle signatures of low-thrust propulsion and space-weather-driven drag variations. The 41 percentage-point improvement in low-thrust maneuver detection validates PhysicsCore's ability to distinguish intentional maneuvering from natural perturbations—a capability critical for assessing adversary intent. FORGE QBit's QuantumSolve optimization module additionally supports conjunction probability calculations at scale across the 45,000+ tracked object catalog.

6.2 FORGE Kinetic — Multi-Phenomenology Sensor Fusion

FORGE Kinetic's Perceive module manages the advanced data fusion engine. Sensor bias correction, statistical data cleansing, time synchronization, and uncertainty quantification across radar, optical, and RF sources are implemented within FORGE Kinetic's sensor abstraction layer. The dynamic weighting of observations based on sensor reliability, observation geometry, and data timeliness exemplifies FORGE Kinetic's resilient multi-source fusion philosophy. The 99.2% catalog accuracy across 45,000+ objects demonstrates FORGE Kinetic's ability to maintain unified state estimates from heterogeneous, asynchronous sensor inputs.

6.3 FORGE QBit — Secure Space Communications

FORGE QBit's CryptoShield framework secures all data flows between SATWATCH and the USSF Space Command and Control (Space C2) system. Post-quantum cryptographic protocols protect conjunction event data, maneuver assessments, and P_c calculations transmitted via REST APIs and Kafka message queues to the Unified Data Library (UDL). The PQ Double Ratchet protocol ensures forward secrecy for real-time alert channels.

6.4 ForgeEvent Integration

The deployment generates five ForgeEvent types across the FORGE OS event bus:

- `INFERENCE` — Maneuver detection, behavioral classification, and conjunction probability assessments
- `SENSOR` — Fused state vector updates from the Kinetic multi-phenomenology fusion engine
- `PHYSICS` — PINN trajectory prediction updates and anomaly detection alerts
- `CRYPTO` — Post-quantum key exchanges and secure channel establishment events
- `ALERT` — High-priority conjunction warnings and anomalous behavior notifications

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