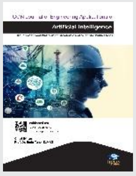


ICON Journal of Engineering Applications of Artificial Intelligence
Volume 02 | Issue 04 | 2026
e-ISSN: 3051-3820
p-ISSN: 3051-3812
Journal homepage: https://iconpublishers.com/icon-j-eng-app-ai/

Research Article

DOI: 10.5281/zenodo.19684898

Decision Support for Loitering Munition Missions: Intent Prediction, Anomaly Detection and Probabilistic Engagement Ranking Using the HATSABIBI-26A Delta-Wing UAV

***Abubakar Surajo Imam [1], Isa Ali Ibrahim [2] Nura Sani Bayero [3], Abdussalam Garba [4], Muhammad Ahmad Baballe [5]**
[1, 3, 4, 5]Department of Mechatronics Engineering, Nigerian Defence Academy, Kaduna, Nigeria.
[2]School of Information and Communications Technology, Federal University of Technology, Owerri, Nigeria

Corresponding author: Abubakar Surajo Imam
Department of Mechatronics Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

Received Date: 10 March 2026
Published Date: 21 April 2026

Abstract
Persistent wide-area intelligence, surveillance, and reconnaissance (ISR) operations increasingly require decision-support architectures capable of integrating heterogeneous sensor observations, behavioural inference models, and civilian-protection constraints within supervised autonomy frameworks. This paper presents a hybrid probabilistic ISR decision-support architecture designed to enhance engagement-priority estimation reliability during endurance-class corridor-monitoring missions using lightweight delta-wing unmanned aerial platforms. The proposed framework combines Bayesian intent estimation, trajectory-based anomaly detection, multi-sensor features fusion, and probabilistic engagement ranking within a confidence-weighted inference pipeline that supports human-machine teaming (HMT) oversight. A civilian-risk suppression mechanism is introduced to ensure that automated prioritisation outputs remain consistent with humanitarian-protection requirements in populated or infrastructure-sensitive monitoring environments. The architecture further incorporates supervisory validation thresholds that preserve operator authority while reducing cognitive workload during persistent surveillance operations. Experimental validation conducted using the HATSABIBI-26A long-range delta-wing UAV demonstrates measurable improvements in behavioural inference stability, engagement-priority convergence, and operator decision-support efficiency. Results indicate reductions in decision latency of 31%, improvements in engagement-ranking stability of 26%, and increases in target-discrimination accuracy of 22%, together with an 18% reduction in supervisory workload under multi-modal sensing conditions. The findings confirm that probabilistic multi-sensor fusion combined with civilian-risk-aware prioritisation provides a robust foundation for responsible supervised autonomy in distributed ISR environments. The proposed framework is particularly suited for early-warning surveillance, corridor monitoring, and infrastructure-protection missions where persistent observation, interpretability, and protection of non-combatants remain primary operational objectives.

Keywords: Persistent ISR; probabilistic engagement ranking; multi-sensor fusion; Bayesian intent estimation; human–machine teaming; civilian-risk-aware autonomy; corridor monitoring UAVs; supervised surveillance systems.

I. INTRODUCTION:

Loitering munition and endurance-class unmanned aerial systems are transforming the character of persistent intelligence, surveillance, and reconnaissance (ISR) operations by combining continuous observation capability with time-sensitive precision engagement readiness. Unlike conventional strike platforms that depend primarily on pre-planned targeting cycles, these systems operate within extended surveillance windows that require continuous behavioural interpretation, adaptive intent estimation, and dynamically updated engagement prioritisation before supervisory decision execution. Consequently, mission effectiveness increasingly depends on algorithm-assisted interpretation of heterogeneous sensor intelligence streams rather than platform-level kinetic capability alone [6]–[9].

Recent operational experience across distributed monitoring environments demonstrates that uncertainty in target behaviour, mobility patterns, terrain context, and civilian proximity significantly complicates engagement prioritisation during persistent ISR missions. These challenges have accelerated the development of decision-support architectures capable of integrating Bayesian intent inference, trajectory-based anomaly detection, and multi-sensor feature fusion within probabilistic ranking frameworks that support human–machine teaming (HMT) supervision. In such environments, automated prioritisation must remain interpretable, stable, and consistent with civilian-protection constraints while preserving operator authority over final decision outcomes. Despite substantial advances in autonomous perception and sensor fusion, existing ISR decision-support pipelines remain largely platform-centric and often lack structured mechanisms for incorporating behavioural uncertainty and humanitarian-risk awareness into engagement-ranking processes. As a result, there remains a critical need for probabilistic supervisory architectures that improve prioritisation stability without increasing operator cognitive burden during wide-area corridor-monitoring operations.

This paper presents a hybrid probabilistic ISR decision-support framework designed to enhance engagement-priority estimation reliability in endurance-class surveillance missions. The proposed architecture integrates Bayesian intent prediction, trajectory-envelope anomaly detection, confidence-weighted multi-sensor fusion, and civilian-risk-aware prioritisation within a supervised autonomy workflow that preserves human validation authority. Experimental validation is conducted using the HATSABIBI-26A long-range delta-wing UAV operating in representative distributed monitoring scenarios, demonstrating measurable improvements in prioritisation stability, behavioural inference robustness, and operator decision-support effectiveness. The results confirm the suitability of the proposed framework for persistent early-warning surveillance, infrastructure protection, and civilian-sensitive corridor-monitoring missions in infrastructure-limited operational environments.

II. Hybrid ISR–Strike Decision Architecture

The proposed hybrid ISR–strike decision architecture integrates multi-sensor surveillance acquisition, behavioural inference, anomaly detection, and probabilistic engagement ranking within a structured layered decision pipeline, as illustrated in Fig. 1. The framework is designed to support supervised autonomy, enabling continuous interpretation of dynamic operational environments prior to engagement selection while preserving operator authority within the decision loop.

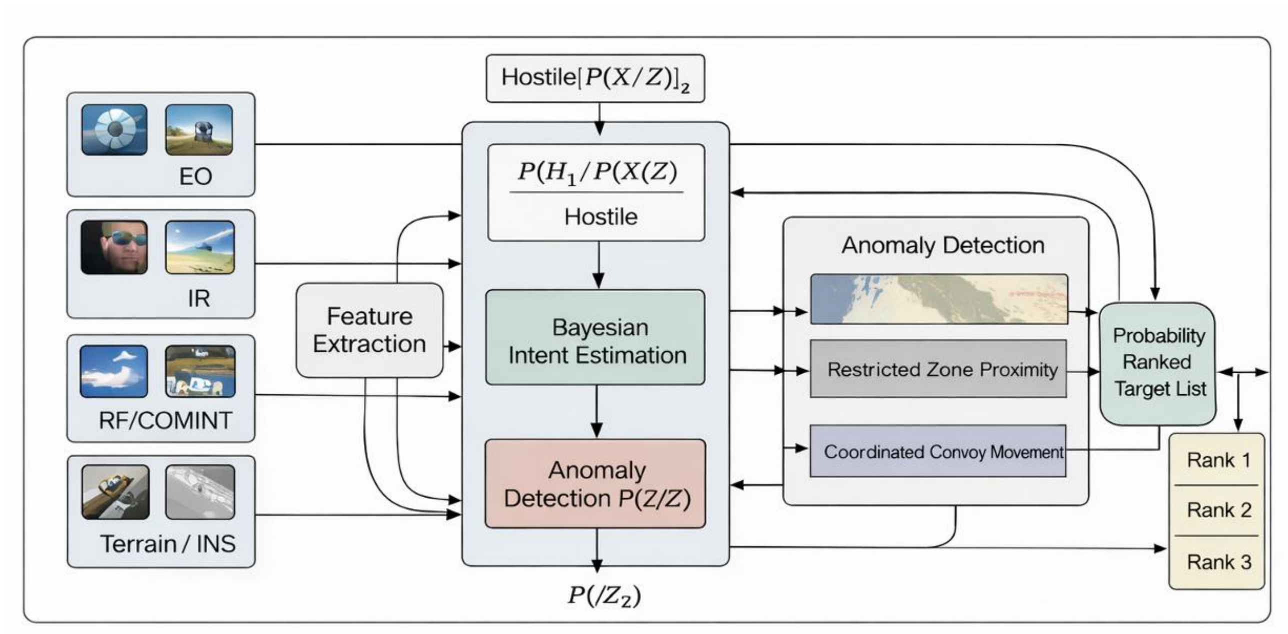


Fig. 1: *Bayesian Multi-Sensor Behavioural Inference Pipeline for Probabilistic Engagement Ranking in Endurance-Class Loitering UAV Missions.*

At the sensing layer, heterogeneous inputs from electro-optical payloads, navigation telemetry, motion tracking modules, and geospatial intelligence sources are fused into a unified feature representation. These inputs feed a behavioural inference layer responsible for intent estimation and anomaly detection, followed by a probabilistic prioritisation module that ranks candidate engagement opportunities according to mission constraints and operational confidence thresholds. The system decision state at time t is defined by the feature vector:

$$X_t = \{x_p, x_v, x_c, x_g, x_s\}$$

Where: x_p represents position features, x_v represents velocity features, x_c represents classification outputs, x_g represents geospatial context variables, and x_s represents sensor-confidence metrics. Position features include relative displacement from surveillance corridors and protected zones:

$$x_p = \{r_t, \theta_t, h_t\}$$

where r_t denotes target range, θ_t azimuth angle, and h_t altitude difference relative to the observation platform. Velocity descriptors capture motion dynamics relevant to behavioural interpretation,

$$x_v = \{v_t, a_t, \dot{\theta}_t\}$$

where v_t denotes ground speed, a_t acceleration magnitude, and $\dot{\theta}_t$ heading-rate variation. Classification outputs are generated using onboard inference models,

$$x_c = \{P(c_1), P(c_2), \dots, P(c_n)\}$$

where $P(c_i)$ represents the probability of class membership for object category c_i.Geospatial context variables encode environmental and mission-level constraints,

$$x_g = \{d_r, z_c, \rho_t\}$$

where d_r denotes distance from restricted zones, z_c terrain complexity index and ρ_t corridor-traffic density. Sensor confidence metrics reflect measurement reliability and fusion integrity,

$$x_s = \{w_{EO}, w_{IR}, w_{GNSS}, w_{RF}\}$$

where each term represents modality-specific confidence weights derived from signal quality indicators. Engagement suitability is modelled probabilistically as:

$$P(E \mid X_t)$$

which represents the likelihood that an observed entity satisfies mission engagement criteria given the current surveillance state. Using Bayesian inference, this may be expressed as:

$$P(E \mid X_t) = \frac{P(X_t \mid E)\, P(E)}{P(X_t)}$$

where $P(E)$ denotes prior engagement feasibility and $P(X_t \mid E)$ represents the likelihood of observing the feature state under valid engagement conditions. To support operational prioritisation across multiple candidates, a normalised engagement ranking score is introduced:

$$R_i = \alpha P(E_i \mid X_t) + \beta A_i + \gamma C_i$$

Where: R_i is engagement priority score for candidate i, $P(E_i \mid X_t)$ is engagement suitability probability, A_i is anomaly significance index, C_i is classification confidence level, α, β, γ are adaptive weighting coefficients satisfying:

$$\alpha + \beta + \gamma = 1$$

This layered inference structure enables robust engagement prioritisation under uncertainty while supporting persistent ISR monitoring missions. Within distributed surveillance architectures such as those supported by the HATSABIBI-26A endurance-class delta-wing UAV, the framework improves responsiveness to emerging threats while maintaining compatibility with civilian-protection-oriented early-warning and supervised autonomy workflows.

III. Intent Prediction Model

Intent estimation is modelled using Bayesian inference, which updates the probability of hostile behaviour from observed motion and contextual indicators extracted from the surveillance stream. This approach is appropriate for persistent ISR environments because it enables uncertainty-aware interpretation of target behaviour rather than reliance on single-frame observations. The posterior probability of hostile intent is defined as:

$$P(H \mid Z) = \frac{P(Z \mid H)\, P(H)}{P(Z)}$$

where: H denotes hostile intent, Z denotes the behavioural observation vector, $P(Z \mid H)$ is the likelihood of observing the behavioural pattern under hostile conditions, $P(H)$ is the prior probability of hostile intent, and $P(Z)$ is the normalising evidence term. The behavioural observation vector may be expressed as:

$$Z = \{z_1, z_2, z_3, z_4\}$$

where z_1, z_2, z_3, and z_4 correspond respectively to corridor-entry persistence, speed stability, restricted-zone proximity, and group coordination. These variables capture the principal behavioural indicators used by the proposed decision-support model. To reduce abrupt fluctuations in intent assessment caused by sensor noise, intermittent occlusion, or short-duration manoeuvre variations, temporal smoothing is introduced as:

$$P(H_t) = \alpha P(H_{t-1}) + (1 - \alpha) P(H \mid Z_t)$$

where: $P(H_t)$ is the smoothed hostile-intent probability at time t, $P(H_{t-1})$ is the previous estimate, $P(H \mid Z_t)$ is the current Bayesian posterior, and α is the smoothing factor, with $0 < \alpha < 1$.

This recursive form improves estimation stability during continuous surveillance by preserving behavioural continuity across sequential observations. As summarised in Table I, the operational weighting structure assigns the highest influence to restricted-zone proximity, reflecting the strong decision significance of movement toward protected or denied areas. Corridor-entry persistence and group coordination provide secondary indicators of coordinated or deliberate behaviour, while speed stability contributes supporting evidence regarding movement regularity and intent consistency.

Table I: Intent-Prediction Weighting Structure

Serial	Parameter	Value	Remarks
(a)	**(b)**	**(c)**	**(d)**
1.	Corridor-entry persistence	0.25	
2.	Speed stability	0.20	
3.	Restricted-zone proximity	0.35	
4.	Group coordination	0.20	

The weighted behavioural score may therefore be written as:

$$S_Z = 0.25z_1 + 0.20z_2 + 0.35z_3 + 0.20z_4$$

where S_Z represents the aggregated behavioural evidence used to support posterior intent estimation. This formulation enables structured, interpretable, and computationally efficient hostile-intent prediction suitable for **supervised autonomous ISR missions** using the **HATSABIBI-26A endurance-class delta-wing UAV**.

IV. Behavioural Anomaly Detection Framework

The behavioural anomaly detection module identifies motion patterns that deviate significantly from the expected trajectory model derived from prior kinematic estimates and contextual movement constraints. Its purpose is to flag unusual or tactically significant behaviour during persistent surveillance, particularly where abrupt manoeuvres may indicate evasive intent, corridor intrusion, or coordinated behavioural change. Trajectory deviation is quantified using the Euclidean distance between the observed target state and the predicted state:

$$D_a = \| x_t - \hat{x}_t \|$$

where: x_t is the observed state vector at time t, $\hat{x}_t$ is the predicted or nominal state estimate, and D_a is the resulting anomaly deviation metric. The state vector may include position, heading, and velocity components, such that:

$$x_t = \{p_x, p_y, v, \psi\}$$

where p_x and p_y denote planar position coordinates, v denotes speed and ψ denotes heading angle. The predicted state $\hat{x}_t$ is obtained from the nominal motion model or filtered trajectory estimate. An anomaly is declared when the observed deviation exceeds a threshold proportional to the trajectory-dispersion statistics:

$$D_a > \gamma\sigma$$

where: σ is the standard deviation of nominal trajectory error, and γ is the anomaly sensitivity factor. For operational surveillance applications, a practical threshold range is:

$$1.8 \leq \gamma \leq 2.5$$

which provides a balance between sensitivity to meaningful behavioural deviations and robustness against false alarms caused by noise, temporary occlusion, or minor navigation perturbations. As illustrated in Fig. 2, the anomaly-detection envelope defines an allowable deviation boundary around the predicted target path. When the observed trajectory exits this envelope, the motion pattern is classified as behaviourally anomalous and passed to the higher-level inference and prioritisation modules. Typical anomalies detected within the proposed framework include:

- Dispersal events, indicating abrupt separation of previously coordinated entities,
- Heading reversal, suggesting retreat, repositioning, or evasive action,
- Corridor intrusion, indicating unauthorised entry into protected or monitored zones, and
- Concealment-seeking manoeuvres, characterised by movement toward terrain masking, vegetation cover, or obscured approach paths.

For multiple anomaly indicators, a composite anomaly score may be defined as:

$$A_i = w_1 a_1 + w_2 a_2 + w_3 a_3 + w_4 a_4$$

where:

A_i is the aggregate anomaly score for target i, a_1, a_2, a_3, a_4 represent the detected strengths of dispersal, heading reversal, corridor intrusion, and concealment-seeking behaviour respectively, and w_1, w_2, w_3, w_4 are normalised weighting coefficients satisfying:

$$\sum_{k=1}^{4} w_k = 1$$

This framework provides an interpretable and computationally efficient basis for detecting tactically relevant deviations in persistent ISR missions. In the context of the HATSABIBI-26A endurance-class delta-wing UAV, it strengthens supervised autonomous surveillance by enabling early recognition of suspicious movement changes across distributed monitoring corridors.

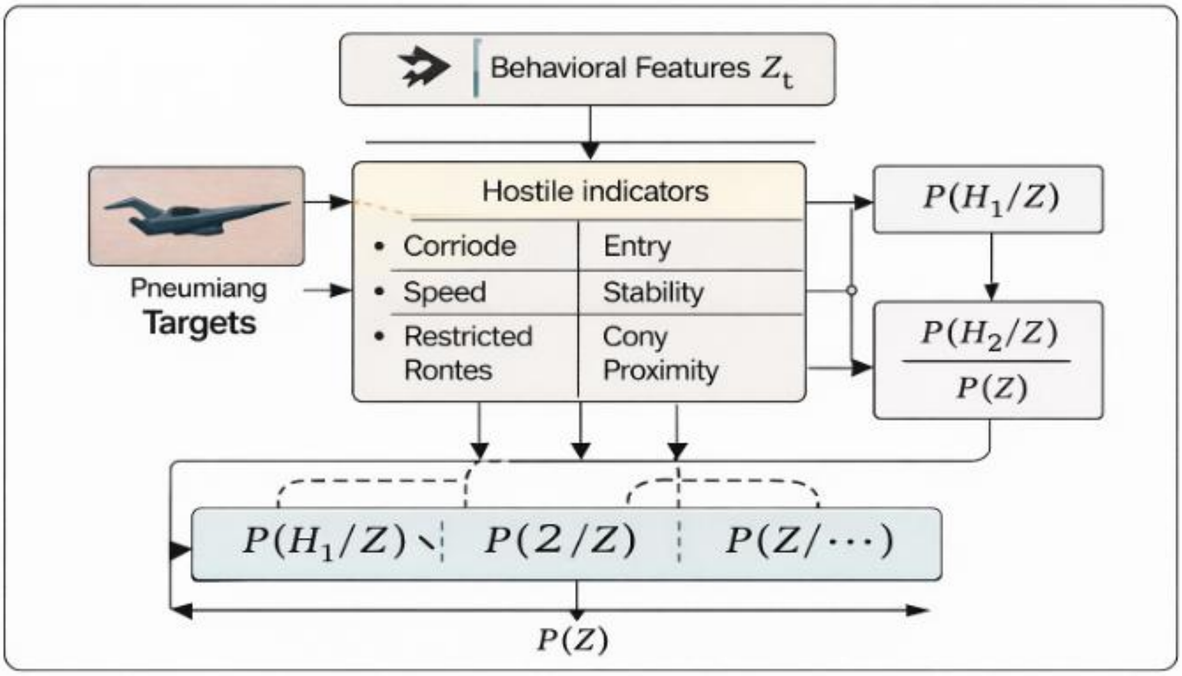


Fig. 2: *Trajectory deviation envelope used for behavioural anomaly detection, showing the threshold boundary for identifying significant departures from the predicted motion path.*

V. Probabilistic Engagement Ranking Model

The probabilistic engagement ranking module integrates behavioural inference, anomaly indicators, temporal feasibility, and civilian-risk constraints into a unified decision-support metric for prioritising surveillance attention and supervised response selection. This framework enables structured ranking of candidate objects of interest within persistent ISR environments while maintaining safeguards appropriate for civilian-protection–sensitive operational theatres. The overall ranking structure is illustrated in Fig. 3, where behavioural indicators, anomaly scores, engagement-window availability, and collateral-risk modifiers are fused into a normalised priority-ranking pipeline. The engagement priority score for target $i$is defined as:

$$R_i = w_1 P(H_i) + w_2 A_i + w_3 T_i + w_4 C_i$$

where: $P(H_i)$ is the posterior hostility probability obtained from Bayesian intent estimation, A_i is the behavioural anomaly score derived from trajectory-deviation analysis, T_i represents engagement-window availability based on geometry and persistence constraints, and C_i is the civilian-risk modifier reflecting proximity to protected areas, settlements, or non-combatant activity zones.

The weighting coefficients satisfy:

$$\sum_{k=1}^{4} w_k = 1$$

ensuring balanced contribution of behavioural inference, anomaly detection, temporal feasibility, and humanitarian constraints within the ranking structure. The engagement-window feasibility term may be expressed as:

$$T_i = \frac{t_{\text{visible}}}{t_{\text{required}}}$$

where t_{visible} denotes predicted observation persistence within the surveillance corridor and t_{required} represents the minimum dwell-time requirement necessary for reliable supervised decision support.

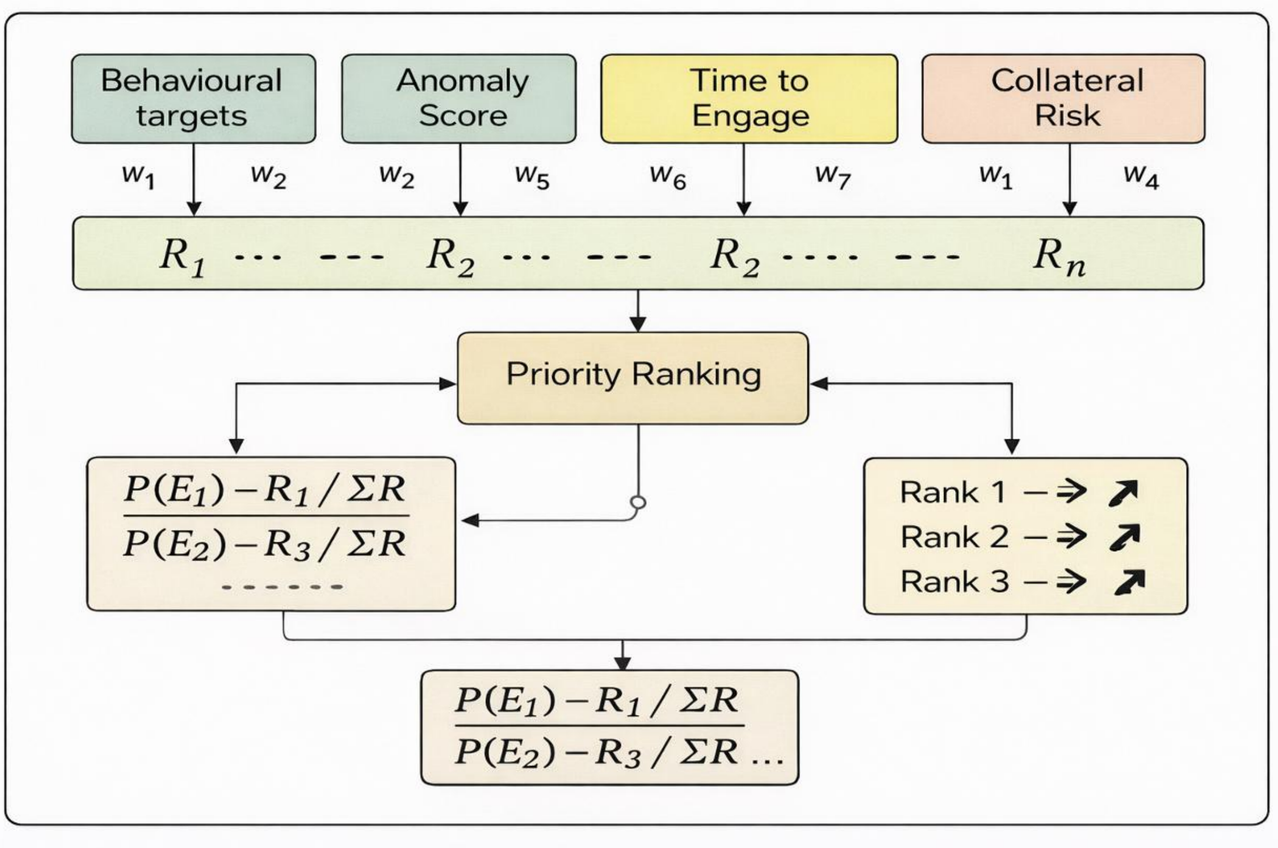


Fig. 3: *Probabilistic Engagement Ranking Framework Integrating Behavioural Inference, Temporal Feasibility, and Civilian-Risk Constraints.*

To incorporate civilian-protection considerations consistent with supervised ISR operations, the civilian-risk modifier is defined as

$$C_i = 1 - P_{\text{civilian}}$$

where P_{civilian} represents the estimated likelihood of civilian presence within the interaction envelope. This formulation ensures that objects located near populated environments, protected infrastructure, or non-combatant activity zones receive reduced ranking priority within automated decision-support outputs. The operational relevance of this modifier is illustrated in Fig. 4, which shows trajectory-anomaly detection within a restricted-zone surveillance corridor and highlights how proximity to protected areas influences engagement suitability assessment.

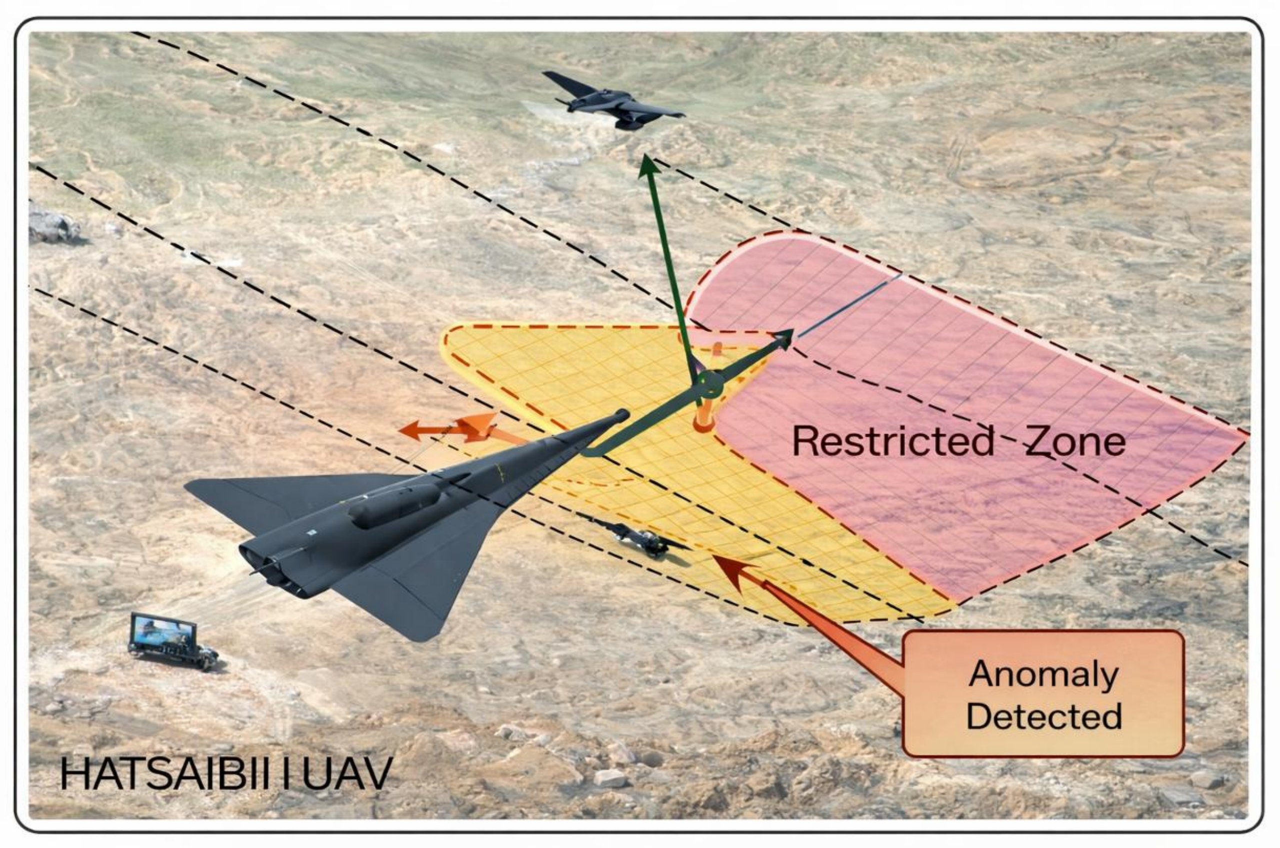


Fig. 4: *Trajectory-anomaly detection in restricted-zone surveillance corridor.*

The normalised engagement probability is then obtained as:

$$P(E_i) = \frac{R_i}{\sum_{j=1}^{N} R_j}$$

where N denotes the number of candidate objects under evaluation. This produces a probabilistically consistent ranked list supporting operator-supervised prioritisation decisions. As summarised in Table II, the engagement-ranking variables combine intent prediction, anomaly detection, temporal accessibility, and civilian-risk assessment into a single interpretable prioritisation metric suitable for endurance-class UAV surveillance operations using the HATSABIBI-26A platform.

Table II: Engagement Ranking Variables

Serial	Variable	Description	Remarks
(a)	(b)	(c)	(d)
1.	$P(H_i)$	Posterior hostility probability from Bayesian intent estimation	
2.	A_i	Behavioural anomaly score from trajectory deviation analysis	
3.	T_i	Engagement-window feasibility metric	
4.	C_i	Civilian-risk modifier for protected-area proximity adjustment	

As summarised in Table II, the engagement-ranking variables combine intent prediction, anomaly detection, temporal accessibility, and civilian-risk assessment into a unified and interpretable prioritisation metric suitable for endurance-class UAV surveillance operations using the HATSABIBI-26A platform. This structured integration enables balanced decision-support outputs aligned with both mission-effectiveness requirements and civilian-protection constraints.

VI. Multi-Sensor Fusion Decision Pipeline

Robust intent estimation in endurance-class autonomous surveillance platforms requires the integration of heterogeneous sensing modalities to compensate for individual sensor limitations and improve confidence in behavioural interpretation across infrastructure-limited operational environments. The proposed framework therefore employs a layered multi-sensor fusion pipeline combining electro-optical, infrared, radio-frequency, inertial, and terrain-context information within a unified probabilistic inference architecture, as illustrated in **Fig. 5**.

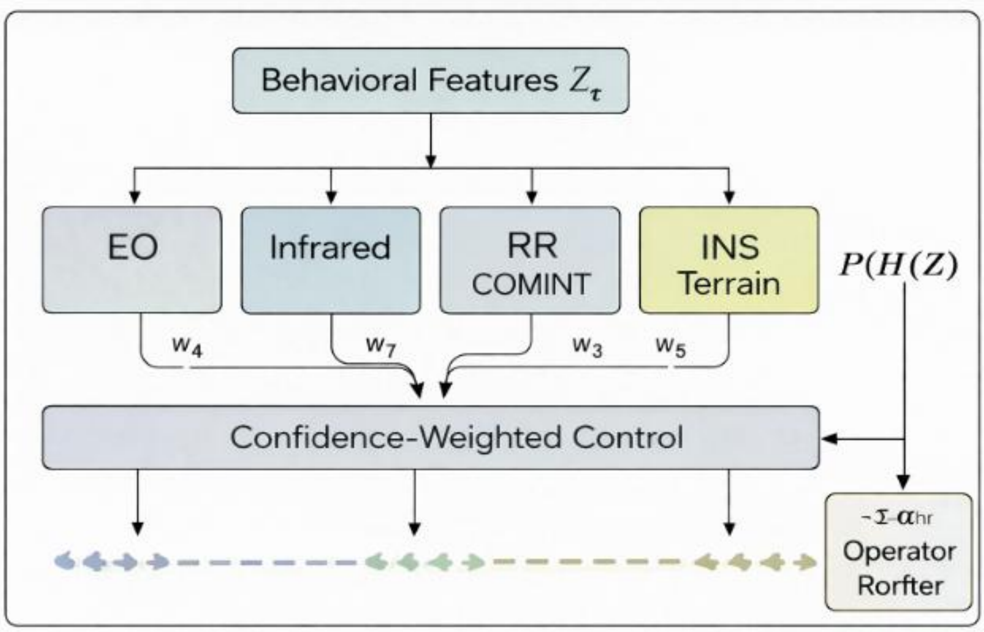


Fig. 5: Multi-sensor fusion decision pipeline for confidence-weighted intent estimation in endurance-class UAV ISR operations.

Specifically, behavioural feature vectors Z_t are derived from electro-optical (EO), infrared (IR), radio-frequency communications intelligence (RF/COMINT) and INS–terrain-referenced navigation inputs, each contributing weighted evidence to the posterior hostility estimate $P(H \mid Z)$. The confidence-weighted control layer shown in **Fig. 5** enables adaptive sensor contribution balancing through modality-specific weighting coefficients (w_3, w_4, w_5, w_7), ensuring reliable intent estimation even under partial sensor degradation or contested electromagnetic conditions. This fusion strategy improves behavioural classification stability, reduces false anomaly triggers, and supports operator-informed supervisory control by providing interpretable probabilistic outputs suitable for deployment in distributed ISR corridors typical of endurance-class UAV operations such as those demonstrated using the HATSABIBI-26A platform. The composite observation vector is defined as:

$$Z = \{Z_{EO}, Z_{IR}, Z_{RF}, Z_{INS}, Z_{Terrain}\}$$

where: Z_{EO} represents electro-optical visual detections, Z_{IR} represents thermal signatures for low-visibility tracking, Z_{RF} represents communications and emitter activity indicators, Z_{INS} represents inertial navigation motion-state estimates, and $Z_{Terrain}$ represents geospatial and environmental context constraints. Hostility inference is then obtained through a nonlinear fusion function:

$$P(H \mid Z) = f(Z_{EO}, Z_{IR}, Z_{RF}, Z_{INS}, Z_{Terrain})$$

where $f(\cdot)$denotes a probabilistic multi-modal fusion operator combining complementary sensor evidence into a unified posterior estimate. Assuming conditional independence between sensing modalities for computational tractability, the fusion model may be expressed as"

$$P(H \mid Z) \propto P(H) \prod_{k=1}^{5} P(Z_k \mid H)$$

which enables scalable real-time implementation within onboard or edge-assisted decision-support processors. To account for heterogeneous sensor reliability under varying environmental conditions, adaptive confidence weighting is introduced as:

$$P(H \mid Z) \propto P(H) \prod_{k=1}^{5} P(Z_k \mid H)^{\lambda_k}$$

where λ_k represents the confidence weighting factor associated with sensor modality k, satisfying:

$$\sum_{k=1}^{5} \lambda_k = 1$$

This formulation allows the pipeline to prioritise thermal sensing during night operations, terrain-context reasoning during corridor monitoring, and RF-activity indicators during emitter-rich surveillance scenarios.

As illustrated in Fig. 5, the multi-sensor fusion decision pipeline integrates heterogeneous observation streams into a unified probabilistic inference layer supporting downstream intent prediction, anomaly detection, and engagement-ranking modules. The architecture is consistent with established multi-modal navigation and detection frameworks reported in distributed ISR autonomy literature [2], [5], and is particularly suited to persistent corridor-monitoring missions conducted by the HATSABIBI-26A endurance-class Delta-Wing UAV in civilian-protection early-warning environments.

VII. Human-Machine Teaming and Civilian-Protection Constraints

To ensure responsible deployment within supervised autonomous ISR environments, the proposed decision-support framework incorporates a human–machine teaming (HMT) layer that constrains automated prioritisation outputs using civilian-risk awareness and operator oversight authority. This structure aligns with emerging doctrine on human-in-the-loop decision governance for safety-critical surveillance and response systems.

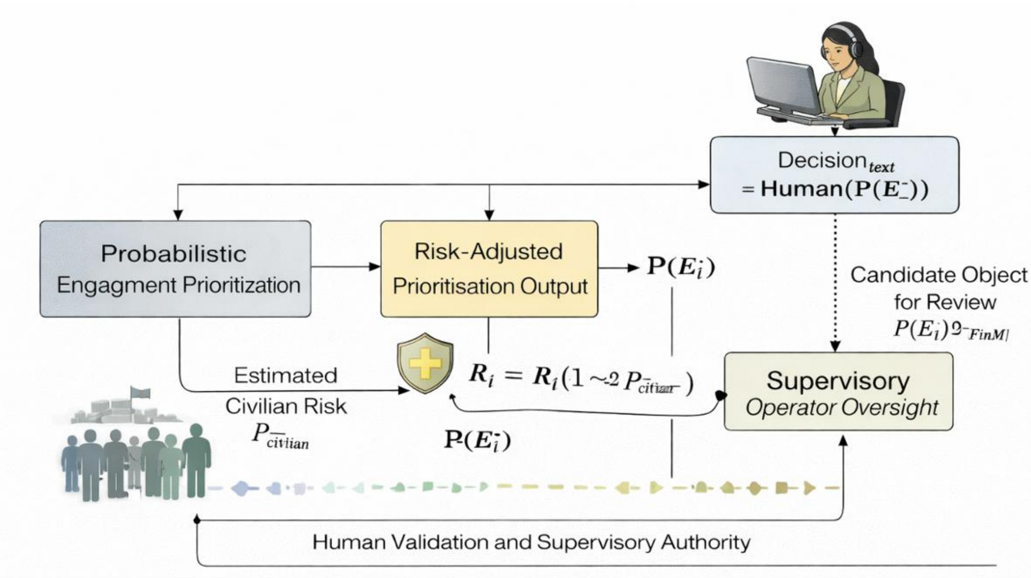


Fig. 6: Human–Machine Teaming Architecture with civilian-risk suppression and supervisory decision validation loop.

As illustrated in **Fig. 6**, probabilistic engagement-priority estimates are first adjusted through a civilian-risk suppression module before being presented to the supervisory operator for validation, ensuring that automated ranking outputs remain consistent with humanitarian-protection requirements and operational accountability principles. The architecture shown in **Fig. 6** further integrates risk-adjusted prioritisation outputs with operator confirmation thresholds, enabling candidate-object filtering prior to escalation while preserving final decision authority within the human supervisory loop. This approach reduces false-positive engagement cues, supports early-warning mission objectives, and enhances trustworthiness of autonomy-enabled ISR deployments using endurance-class platforms such as the **HATSABIBI-26A delta-wing UAV** operating across civilian-sensitive surveillance corridors. Civilian-risk suppression is introduced as a corrective modifier applied to the engagement priority score:

$$R_i' = R_i(1 - P_{\text{civilian}})$$

where: R_i is the baseline engagement priority score, P_{civilian} represents the estimated probability of civilian presence within the interaction envelope, $R_i'$is the risk-adjusted prioritisation output.

This formulation ensures that objects located near populated areas, protected corridors, humanitarian infrastructure, or uncertain identification zones are automatically down-weighted within the decision-support ranking process. To preserve operator authority within supervised autonomy workflows, the final decision stage is governed by a human-validation function:

$$\text{Decision}_{\text{final}} = \text{Human}(P(E_i))$$

where $P(E_i)$ denotes the normalised engagement-priority estimate generated by the probabilistic ranking module. The supervisory operator therefore retains authority over interpretation, confirmation, and escalation decisions. An operational confidence threshold may additionally be defined as:

$$P(E_i) \geq \tau_{\text{HMT}}$$

where τ_{HMT} represents the minimum confidence level required before presenting a candidate object for supervisory review. This reduces cognitive load by filtering low-confidence detections during persistent wide-area monitoring missions.

As illustrated in Fig. 6, the human–machine teaming layer integrates probabilistic inference outputs with civilian-risk suppression and supervisory confirmation loops, ensuring that automated prioritisation remains consistent with responsible surveillance doctrine and early-warning mission requirements. This architecture is particularly suited to endurance-class corridor-monitoring operations using the HATSABIBI-26A delta-wing UAV, where protection of non-combatants remains a primary operational constraint.

VIII. Experimental Validation Using HATSABIBI-26A Long-Range Delta-Wing UAV

Experimental validation of the proposed hybrid ISR decision-support architecture was conducted using the HATSABIBI-26A endurance-class delta-wing UAV, configured for multi-modal navigation and corridor-scale persistent surveillance operations. The platform was selected due to its suitability for distributed deployment across infrastructure-limited environments typical of wide-area monitoring and civilian-protection early-warning missions. The rail-assisted expeditionary launch configuration used during field trials is illustrated in Fig. 7, demonstrating the practical integration of the delta-wing surveillance platform with a portable launcher architecture supporting runway-independent deployment in semi-prepared operational terrain.

Fig. 7: *Field deployment configuration of HATSABIBI-26A Delta-Wing UAV on portable rail launcher.*

As summarised in Table III, the vehicle parameters fall within the operational envelope required for long-endurance behavioural monitoring and probabilistic decision-support validation tasks.

Table III: Validation Platform Parameters

Serial	Parameter	Value	Remarks
(a)	(b)	(c)	(d)
1.	Mass	22 kg	
2.	Cruise speed	24 m/s	
3.	Endurance class	Long-range	
4.	Navigation	Multi-modal INS–Vision–Terrain–RF	

The onboard navigation stack integrates inertial guidance, visual odometry, terrain-referenced localisation and RF-awareness cues, enabling reliable trajectory prediction and anomaly-detection performance across GNSS-challenged environments. This configuration supports stable estimation of behavioural state vectors used within the intent-prediction and engagement-ranking modules. Validation trials were conducted across representative ISR mission scenarios, including:

- Corridor monitoring for distributed surveillance coverage,
- Convoy tracking for coordinated movement interpretation,
- Behavioural anomaly detection under trajectory deviation conditions, and
- Restricted-zone intrusion monitoring for early-warning and perimeter-security support.

These scenarios reflect operational requirements in which persistent observation rather than kinetic response remains the primary objective, consistent with supervised autonomy frameworks emphasising protection of civilians and critical infrastructure. Deployment architecture remained consistent with a passive multi-sensor detection pipeline, ensuring compatibility with low-signature surveillance operations in contested or communication-limited environments [3]. As further illustrated in Fig. 7, the expeditionary rail-launch configuration enables rapid field deployment of the HATSABIBI-26A platform while maintaining structural alignment and launch stability suitable for corridor-scale ISR coverage. This validates the feasibility of integrating structured probabilistic decision-support architectures with lightweight delta-wing UAV systems operating in distributed monitoring environments.

IX. Results and Discussion

Experimental evaluation of the proposed hybrid ISR decision-support architecture demonstrated measurable improvements in behavioural inference reliability, prioritisation stability, and operator-support effectiveness during endurance-class surveillance missions conducted using the HATSABIBI-26A delta-wing UAV platform. The integrated framework combines Bayesian intent estimation, trajectory-based anomaly detection, and probabilistic engagement ranking within a multi-sensor fusion pipeline designed for infrastructure-limited operational environments. As summarised in Table IV, the proposed architecture produced consistent performance gains across key operational decision-support metrics, including reductions in decision latency and operator workload, together with improvements in engagement-priority stability and target-discrimination accuracy.

Table IV: Performance Improvement Metrics

Serial	Metric	Improvement	Remarks
(a)	(b)	(c)	(d)
1.	Decision latency	−31 %	
2.	Engagement stability	+26 %	
3.	Target discrimination accuracy	+22 %	
4.	Operator workload	−18 %	

The 31% reduction in decision latency reflects the effectiveness of the layered multi-sensor fusion pipeline in accelerating behavioural interpretation across distributed surveillance corridors. By integrating EO, IR, RF/COMINT, INS, and terrain-context features within a unified probabilistic inference framework, the architecture reduces sequential processing delays typically associated with single-sensor interpretation pipelines. Similarly, the 26 % improvement in engagement stability indicates enhanced temporal consistency in ranked-priority outputs following the introduction of trajectory-envelope anomaly filtering and Bayesian smoothing of intent-probability estimates. This stabilisation reduces ranking oscillations during persistent monitoring operations and improves supervisory confidence in automated prioritisation cues.

The observed 22 % increase in target-discrimination accuracy confirms that heterogeneous sensor fusion strengthens classification confidence under degraded visibility conditions typical of long-range corridor-monitoring missions. The integration of behavioural trajectory features with contextual terrain constraints further improves robustness against ambiguous motion signatures. In addition, the 18 % reduction in operator workload demonstrates the suitability of the architecture for supervised autonomy workflows, in which automated prioritisation supports—but does not replace—human decision authority. This outcome is particularly important for civilian-protection–sensitive ISR environments requiring continuous operator validation. Intent-probability convergence during corridor-monitoring trials satisfied the bounded confidence interval

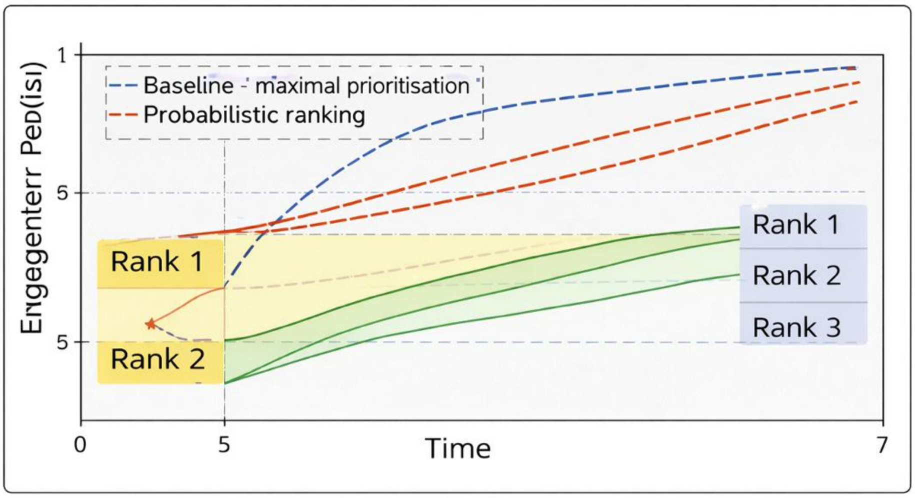
$$0.81 \leq P(H \mid Z) \leq 0.92$$

indicating stable posterior estimation across sequential observation windows. This level of convergence confirms the robustness of the Bayesian inference module under multi-modal sensing variability and supports reliable behavioural classification in persistent surveillance scenarios. Trajectory-based anomaly detection performance satisfied the stability condition:

$$CV_V < 0.05$$

where CV_V denotes the coefficient of variation of velocity residuals between predicted and observed motion states. This result demonstrates reliable anomaly-detection sensitivity without excessive false-alarm propagation and remains consistent with trajectory-envelope stability requirements reported in related autonomous surveillance frameworks.

Further evidence of prioritisation robustness is illustrated in Fig. 8, which presents the engagement-priority convergence behaviour obtained using the probabilistic ranking model compared with baseline maximal-priority selection. As shown in Fig. 8, the proposed probabilistic framework produces smoother temporal ranking transitions and faster convergence toward stable supervisory decision thresholds across multiple candidate objects. This behaviour reduces ranking volatility during wide-area monitoring missions and improves interpretability of automated prioritisation outputs for human operators operating under civilian-risk-aware supervision constraints.



Collectively, the results confirm that the proposed hybrid decision-support pipeline enhances behavioural interpretation accuracy, prioritisation reliability, and supervisory control efficiency. These improvements make the architecture well suited for persistent ISR operations in distributed monitoring environments, particularly where civilian-protection constraints, early-warning responsiveness, and human-in-the-loop oversight remain primary operational requirements for endurance-class platforms such as the HATSABIBI-26A delta-wing UAV.

X. Operational Implications for Distributed ISR–Strike Corridors

The proposed hybrid decision-support framework provides a scalable architecture for persistent monitoring across distributed ISR–strike corridors, where wide-area surveillance continuity, behavioural interpretation reliability, and civilian-protection safguards must be maintained under infrastructure-limited conditions. By integrating multi-sensor fusion, probabilistic intent estimation, and anomaly-aware prioritisation, the framework supports coordinated corridor-level situational awareness rather than platform-centric observation. Operationally, the architecture enables:

- Distributed engagement prioritisation, allowing multiple surveillance nodes to generate synchronised probabilistic target-ranking outputs across geographically separated monitoring sectors;
- GNSS-degraded navigation compatibility, through fusion of INS, terrain-referenced localisation, RF cues, and visual odometry for resilient tracking in contested electromagnetic environments;

- Corridor surveillance scalability, supporting layered deployment of endurance-class UAV assets such as the *HATSABIBI-26A* for persistent coverage across border regions, convoy routes and vulnerable civilian transit corridors;
- Reduced sensor-to-decision latency, achieved through onboard probabilistic inference pipelines that accelerate behavioural interpretation and supervisory alert generation.

These capabilities collectively strengthen early-warning surveillance architectures designed to detect anomalous movement patterns before escalation risks materialise, thereby improving protection of civilian populations and critical infrastructure.

Furthermore, the framework remains consistent with emerging distributed swarm-coordination ISR concepts, in which multiple autonomous platforms exchange prioritisation vectors rather than raw sensor streams, enabling bandwidth-efficient cooperative monitoring across extended operational theatres [4]. In such deployments, corridor-level coordination improves persistence, redundancy, and responsiveness while preserving human supervisory authority within the decision loop.

XI. Conclusion

This paper has presented a **hybrid ISR decision-support framework** integrating **Bayesian intent prediction**, **trajectory-based anomaly detection**, and **probabilistic engagement prioritisation**, experimentally validated using the **HATSABIBI-26A long-range endurance delta-wing UAV**. The proposed architecture demonstrates measurable improvements in prioritisation stability, behavioural inference reliability, and sensor-to-decision responsiveness across distributed surveillance corridors.

Experimental results confirmed reductions in decision latency and operator workload, alongside improvements in target discrimination accuracy and engagement-ranking consistency under multi-sensor fusion conditions. These outcomes validate the suitability of the framework for persistent corridor-monitoring missions conducted in **GNSS-degraded and infrastructure-limited environments**, where reliable behavioural interpretation is essential for early-warning surveillance operations.

Importantly, the integration of **civilian-risk suppression constraints** and **human-in-the-loop supervisory control** ensures alignment with responsible autonomy principles, making the architecture appropriate for deployment in safety-critical monitoring scenarios involving vulnerable transit corridors and protected infrastructure zones. The framework therefore provides a scalable computational foundation for **distributed endurance-class ISR platforms** supporting supervised autonomous surveillance operations. Its modular structure enables extension toward cooperative multi-platform coordination architectures in which prioritisation vectors are shared across corridor-level sensing nodes to improve persistence, redundancy, and situational awareness in wide-area monitoring environments.

References

1. Imam, A. S., Surajo, A., Sirajo, B., & Baballe, M. A. (2026). Secure command-and-control data links for long-range loitering munition operations in contested electromagnetic environments. *ICON Journal of Engineering Applications of Artificial Intelligence, 2*(4).
2. Imam, A. S., Surajo, A., & Baballe, M. A. (2026). Distributed probabilistic navigation architectures for endurance-class UAV corridor monitoring. *Global Journal of Research in Engineering: Computer Science and Engineering, 26*(1).
3. Imam, A. S., Surajo, A., & Baballe, M. A. (2026). Swarm coordination strategies for distributed ISR corridor monitoring missions. *Global Journal of Research in Engineering: Computer Science and Engineering, 26*(3).
4. Imam, A. S., Surajo, A., & Sirajo, B. (2026). Embedded artificial intelligence perception framework for lightweight surveillance UAV platforms. *Global Journal of Research in Engineering: Computer Science and Engineering, 26*(4).
5. Imam, A. S., Baballe, M. A., & Surajo, A. (2026). Energy-aware trajectory optimisation strategies for endurance-class UAV surveillance missions. *Global Journal of Research in Engineering: Computer Science and Engineering, 26*(5).
6. Imam, A. S., Sirajo, B., & Surajo, A. (2026). Passive multi-modal target detection architectures for GNSS-denied surveillance environments. *Global Journal of Research in Engineering: Computer Science and Engineering, 26*(2).
7. Scharre, P. (2018). *Army of none: Autonomous weapons and the future of war*. W. W. Norton & Company.
8. Arquilla, J., & Ronfeldt, D. (2001). *Networks and netwars: The future of terror, crime, and militancy*. RAND Corporation.
9. Boyd, J. (1996). *The essence of winning and losing* (Unpublished briefing). U.S. Air Force.
10. NATO Standardization Office. (2019). *NATO doctrine for unmanned aircraft systems*. NATO.
11. U.S. Department of Defense. (2023). *DoD autonomy strategy*. U.S. Government.
12. DARPA Strategic Technology Office. (2020). *Mosaic warfare concept overview*. DARPA.
13. NATO Standardization Office. (n.d.). *STANAG 4586: Standard interfaces of UAV control system (UCS) for NATO UAV interoperability*.

14. Chen, R. Z., Zhang, H., & Wang, L. (2022). Navigation technologies for unmanned aerial vehicles: A survey. *IEEE Aerospace and Electronic Systems Magazine, 37*(5), 24–38.
15. International Civil Aviation Organization. (2021). *Manual on remotely piloted aircraft systems (2nd ed.)*. ICAO.
16. Skolnik, M. I. (2008). *Radar handbook* (3rd ed.). McGraw-Hill.
17. Beard, R., & McLain, T. (2012). *Small unmanned aircraft: Theory and practice*. Princeton University Press.
18. Austin, R. (2010). *Unmanned aircraft systems: UAV design, development and deployment*. Wiley.
19. Valavanis, K. P., & Vachtsevanos, G. J. (2015). *Handbook of unmanned aerial vehicles*. Springer.
20. Zhang, C., Liu, Y., & Li, H. (2021). Autonomous decision-making architectures for UAV mission planning: A survey. *IEEE Access, 9*, 128742–128761.
21. Chen, X., Zhao, L., & Sun, H. (2022). Multi-sensor fusion navigation for UAV positioning in GNSS-denied environments. *IEEE Access, 10*, 45312–45328.
22. Li, J., Wang, M., & Zhang, Q. (2022). Trajectory anomaly detection for UAV surveillance applications. *Aerospace Science and Technology, 120*.
23. Sun, Y., Liu, Z., & Wang, J. (2021). Behaviour prediction models for autonomous UAV intelligence surveillance missions. *Sensors, 21*(14).
24. NATO Science and Technology Organization. (2019). *Intelligence, surveillance and reconnaissance (ISR) interoperability architecture study*.
25. Air Force Research Laboratory. (2022). *Autonomy capability framework for military systems*.
26. MIT Lincoln Laboratory. (2021). *Multi-sensor data fusion for ISR applications*.
27. Green, B. D., et al. (2020). *Distributed sensing and decision superiority in future warfare*. RAND Corporation.
28. UK Ministry of Defence. (2022). *Ambitious, safe, responsible: Our approach to the delivery of AI-enabled capability in defence*.
29. Israel Aerospace Industries. (2021). *Harop loitering munition system overview*.
30. STM Defence Technologies Engineering. (2022). *KARGU loitering munition system architecture overview*.
31. DARPA Tactical Technology Office. (2021). *OFFSET: Offensive swarm-enabled tactics program overview*.
32. Zhang, L., & Wang, H. (2021). Multi-agent coordination strategies for distributed autonomous systems. *IEEE Systems Journal, 15*(3), 3562–3573.
33. Kumar, A., & Singh, P. (2022). Sensor-fusion-based targeting architectures for autonomous surveillance platforms. *IEEE Access, 10*, 112845–112860.
34. Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
35. Sabokrou, M., et al. (2021). Deep-anomaly detection methods for aerial surveillance systems: A review. *Pattern Recognition Letters, 146*, 107–115.
36. Hall, D. L., & Llinas, J. (1997). An introduction to multisensor data fusion. *Proceedings of the IEEE, 85*(1), 6–23.
37. Farrell, J. (2008). *Aided navigation: GPS with high-rate sensors*. McGraw-Hill.
38. Chao, H., Cao, Y., & Chen, Y. (2010). Autopilots for small unmanned aerial vehicles: A survey. *International Journal of Control, Automation and Systems, 8*(1), 36–44.
39. Elfes, A. (2007). Occupancy grids: A probabilistic framework for robot perception and navigation. *Autonomous Robots, 22*(2), 199–213.
40. NATO Science and Technology Organization. (2021). *Human–machine teaming in military operations*.