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Human Factors in the Design of Human–Machine Interfaces for Counter-Drone Systems

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ABSTRACT

This paper examines human–machine interfaces (HMIs) for counter-UAS systems and identifies the interaction patterns that most strongly affect operator performance in multi-sensor, time-critical environments. By analysing how operators interpret fused tracks, manage alerts, and verify targets under workload, we highlight key design principles: clear presentation of uncertainty and data freshness, one-action cross-cueing to sensor views, compact evidence bundles that consolidate relevant cues, adaptive visual decluttering during multi-track surges, and alerting schemes that combine severity with confidence while limiting overload. We propose a concise set of HMI-focused performance indicators—time-to-acknowledge, time-to-track, time-to-verification, alert hygiene, interface stability under load, and evidence-bundle completeness—to shift evaluation from sensor-centric to operator-centric metrics. The findings show that effective C-UAS performance depends on interfaces that minimize cognitive friction, compress critical actions, and maintain situational clarity even under stress.

Keywords: Human–machine interface, Counter-UAS, Situational awareness, Operator performance

INTRODUCTION

The rapid global proliferation of small unmanned aerial systems (UAS) has transformed both civilian and military airspace, creating unprecedented challenges for infrastructure protection, public safety, and security operations (Vajravelu, 2023). As off-the-shelf drones become cheaper, more capable, and easier to fly, their misuse has increased sharply. Large-scale incident analyses report hundreds of UAS-related events affecting airports, law-enforcement operations, critical infrastructure, and public gatherings, underscoring the urgency for effective counter-UAS (C-UAS) solutions capable of detecting, tracking, and identifying aerial threats (Buric, 2017).

Modern C-UAS systems are inherently multi-sensor platforms, integrating heterogeneous technologies such as radar, radio-frequency monitoring, electro-optical/infrared imaging, thermal sensors, acoustic arrays, and sometimes lidar (Kang, 2020). Each technology contributes different strengths such as range, accuracy, robustness, or classification capability, and compensates for the limitations of others. However, the operational effectiveness of any C-UAS installation depends not only on the technical performance of its sensors but also on the quality of the human–machine

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interface (HMI) through which operators interpret and act upon sensor data. This dependency is explicitly recognized in standardized C-UAS evaluation frameworks (De Cubber, 2025), which note that the operator interface plays a decisive role in situational awareness, cognitive workload, and the timeliness of threat assessment.

C-UAS operators must perform demanding cognitive tasks under significant time pressure. They must integrate multispectral information, distinguish drones from birds or benign aircraft, resolve contradictory sensor inputs, assess pilot intent, and determine the severity of a situation, often within seconds. These tasks become even more complex under adverse environmental conditions, cluttered electromagnetic environments, or multi-drone scenarios, all of which are explicitly addressed in established C-UAS test methodologies (Petsioti, 2024). The variability and unpredictability of real-world scenarios, including false alarms, rapidly evolving threat vectors, and intermittent sensor loss, place a substantial cognitive burden on operators, increasing the risk of delayed or wrong responses.

Despite the centrality of the human operator, contemporary research and industrial development have often focused predominantly on sensor technology and system performance (Doroftei, 2018), (Brewczyński, 2024), while HMI design, and the human factors that shape system effectiveness, have received comparatively less systematic attention. Yet C-UAS standards (CENELEC, 2024) emphasize that even highly capable sensor suites cannot deliver meaningful operational value if operators struggle to interpret data, maintain situational awareness, or manage multiple concurrent alerts. The integration of artificial intelligence (AI) and machine learning (ML) into C-UAS systems introduces both opportunities and new complexities: automated tracking and classification may reduce workload, but opaque decision logic can undermine operator trust or increase verification time.

This paper examines C-UAS human–machine interfaces from a human-factors perspective, focusing specifically on situational awareness, cognitive workload, and decision latency. Drawing on insights from simulated systems (Doroftei, 2022), operational systems (Doroftei, 2024), and evaluations synthesized during operational C-UAS trials during the COURAGEOUS (De Cubber, 2023) and COURAGEOUS^2 projects, the analysis identifies recurring interface design patterns, usability constraints, and performance bottlenecks that influence operator effectiveness. A central theme is the tension between information richness and cognitive manageability, which is essential for timely and reliable decision-making. By consolidating lessons learned and deriving principles for operator-centred interface design, this paper aims to contribute to support the development of future C-UAS solutions that optimize both technological and human performance.

HUMAN FACTORS CHALLENGES IN C-UAS OPERATIONS

Operator Roles and Tasks Along the C-UAS Kill Chain

Within fixed sites or mobile deployments, human operators supervise C-UAS solutions and coordinate responses with stakeholders (e.g., Air Traffic

Control, site security, first responders). Typical tasks include: (i) monitoring fused displays for alerts and anomalous tracks; (ii) validating detections (bird vs. drone, friendly vs. unknown); (iii) maintaining track continuity and handling handover between sensors; (iv) initiating identification workflows (Pan Tilt Zoom tracking, database checks, payload inference); (v) executing communications/escalation protocols; and (vi) logging events for forensics. Standards call for interfaces that support role-based access, configurable alerts, geofencing, friend/foe distinction, event history and data export, while minimizing unnecessary steps and training burden.

A recurrent requirement is simultaneous multi-target management: operational contexts often involve benign aircraft and birds alongside potential threats. Scenario-driven evaluations recommend stressing systems with tens of concurrent tracks to test prioritization, decluttering, uncertainty visualization, and alert latency—factors directly tied to operator situation awareness and decision speed.

Environmental, Technological and Regulatory Constraints

Environmental variability (rain, fog, glare, wind), terrain/clutter (urban canyons, vegetation), and electromagnetic interference differentially impact sensors and can elevate false alarms or cause intermittent track loss, thereby complicating operator judgement. Radar performance, for example, is impacted by wavelength-dependent attenuation in precipitation; free-space and two-way losses compound with range and frequency.

In the EU, UAS operations are harmonised (through regulations 2019/947–2019/945 and 2021/664–665–666), but there is still no single, horizontal C-UAS regulation; most Member States allow authorised detection while reserving active mitigation to military or specialised police under telecom/spectrum and safety constraints. For HMIs this means the default civilian posture is detect–assess–coordinate: the User Interface must expose the local legal capability set (detection-only vs. detection + mitigation), bind escalation actions to the competent authority, and attach provenance (who/what/when/where) to every operator action for audit/forensics. As U-space deployment is uneven, interfaces should be able to merge services (remote ID, flight authorisations, traffic info) where available with national geo-zone overlays and NOTAMs, while clearly labelling the legal source of each constraint. Because C-UAS data often fall under GDPR/LED and, where AI is used, the AI Act, HMIs must make purpose/retention/role controls, uncertainty disclosure, and human-oversight hooks first-class elements that are visible at the point of action.

Human-Factors Dimensions

This section analyses three core human-factors dimensions that shape C-UAS performance: situational awareness, cognitive workload, and decision latency. These dimensions are deeply interconnected and are influenced by environmental stressors, sensor limitations, automation design, interface quality, and organizational constraints.

Situational Awareness

Situational Awareness (SA), defined classically by (Endsley, 1995) as perception, comprehension, and projection is continuously challenged in C-UAS operations. Operators must synthesize multi-sensor cues (RF, radar, EO/IR, acoustic), each with distinct uncertainties, latencies, and failure modes. Environmental variability (e.g., fog, clutter, multipath), combined with high rates of false alarms or intermittent tracks, undermines perception and interpretation of the tactical picture.

A major SA burden arises from target ambiguity. Small UAS often exhibit signatures similar to birds or aircraft, require cross-verification, and may only be detectable intermittently due to radar line-of-sight occlusion or EO/IR visibility drop-offs. RF-based identification can fail when drones operate in autonomous modes, use non-standard or frequency-hopping links, or reduce emissions.

Automation can help, but only if it is transparent. Opaque ML-based classifiers risk reducing SA through "automation surprises" or false confidence. Research consistently shows that SA degrades if operators cannot understand or predict automated system behaviour. Thus, C-UAS HMIs must expose uncertainty, show classification rationale where feasible, and visualize temporal context (track history, quality, and prediction envelopes).

Cognitive Workload

Cognitive workload in C-UAS operations is driven by multitasking demands, rapid context switching, environmental pressure, and the need to understand inconsistent data streams. Wickens' Multiple Resource Theory (MRT) predicts performance degradation when tasks compete for the same perceptual and cognitive resources (Wickens, 2008). This is highly relevant in C-UAS settings, where operators monitor map displays, radar scopes, EO/IR video, RF analytics, alerts, and communication channels simultaneously.

High-alert environments such as airports, critical infrastructure, and military bases add further strain. False alarms, especially from radar clutter, environmental noise, or non-hostile drones, increase vigilance demands and contribute to fatigue and reduced discrimination accuracy. The workload is further compounded during multi-drone or swarm incursions. Here, poor decluttering, excessive alarm cascades, and non-prioritized displays can drive operators into reactive rather than anticipatory behaviour.

Effective workload management thus requires:

- modality separation (visual vs. auditory cues) aligned with MRT,
- adaptive alerting (rate-limited, priority-weighted),
- automation support that does not obscure operator awareness,
- configurable layouts matching operator roles and site-specific procedures.

Decision Latency

Decision latency is defined as the delay between detection, operator comprehension and action. It is a critical mission metric, as in many high-risk scenarios (e.g., explosive payload delivery, airfield intrusion), operators may only have a few tens of seconds to detect, classify, escalate, and respond.

Latency arises from both system and human contributors. System factors include sensor refresh rates, fusion delays, poor cueing between modalities, and slow interoperability layers in multi-vendor systems. Human factors include high mental workload, incomplete SA, distrust of automation, or excessive verification steps during ambiguous alerts.

Regulatory environments can further increase delay. Airport operators, for example, must coordinate actions under strict rules of engagement that differentiate detection from mitigation and limit local authorities to take kinetic or RF-based actions

Mitigating latency requires:

- clear threat prioritization with visual urgency coding,
- synchronized multi-sensor cueing (e.g., radar → EO tracking),
- operator workflows that minimize clicks and context switching,
- rapid-access escalation channels and automated report templates,
- predictive displays that show likely trajectory and impact windows.

Implications for the Operator Interface

Human-factors limitations remain one of the strongest determinants of C-UAS effectiveness. Poor SA, excessive workload, and long decision latency can nullify even highly capable sensor suites. Conversely, interfaces built around human-centred principles, cognitive ergonomics, and transparent automation can significantly amplify operator performance. These insights motivate the following design recommendations:

- Fused, prioritized visualization with explicit uncertainty/confidence cues to sustain SA under noise/clutter
- Workflow-aligned interaction design (validation, tracking, escalation) that minimizes manual steps at high tempo, consistent with MRT-informed channel separation
- Adaptive automation with explainability (e.g., auto-tracking, cross-cueing, ML classification) to reduce workload without eroding trust
- Scenario-aware configurability for airports, prisons, borders, and events—including geofences, alert rules, and inter-agency sharing aligned with U-space guidance
- Real-time estimated performance telemetry (Probability of Detection, False Alarm Rate, tracking health) surfaced in the UI to calibrate operator confidence and speed decisions.

INTERFACE DESIGN PATTERNS OBSERVED IN EXISTING C-UAS SYSTEMS

This section outlines observed best practices in practical interface design, layout organisation, and workflow shaping that support fast and reliable operator decision-making. To preserve full anonymity and data confidentiality of COURAGEOUS trial participants, the discussion remains system-agnostic and synthesises only global design patterns.

C-UAS interfaces must simultaneously provide clarity, efficiency, and resilience under load. Operators should understand the tactical situation at a glance without navigating through deep menu structures or juggling multiple raw data panels. Equally important is the ability to execute the dominant workflow—validating a detection, confirming its classification, and escalating when necessary—with as few steps as possible. During peaks of activity, when many tracks, alerts, and sensor cues compete for attention, the interface should degrade gracefully, prioritising essentials and minimising clutter to maintain situational control.

A structured information architecture, as shown on Figure 1 helps achieve this balance. A persistent primary layer keeps the map, tracks, geofences, and alerts always visible, forming the operator's core mental frame. Additional detail resides in a secondary layer, opened only when needed, containing EO/IR and radar panels, RF views, and historical timelines. A tertiary layer houses less frequently used tools such as logs, reporting functions, and configuration utilities. This tiered approach prevents overload while enabling operators to access depth on demand.

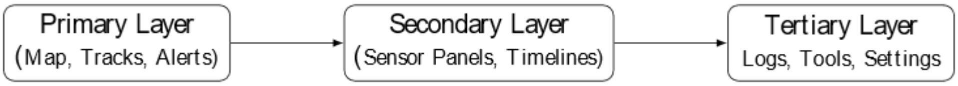

Figure 1: Three-tier information architecture for C-UAS interfaces.

Across this structure, certain visual conventions consistently improve comprehension. Predictive trajectory cones allow operators to anticipate aircraft motion rather than react to it. Track freshness indicators, such as fading halos or subtle colour decay, expose when data is stale, preventing overconfidence in outdated cues. Compact track cards that expand on hover provide immediate access to essential attributes, behaviour cues, and a short event history without overwhelming the main display. Interfaces that show multi-sensor confidence by showing small per-sensor contribution bars or similar cues, help the operator judge how reliable the fused assessment is.

Alerting behaviour must also be shaped carefully. Effective systems present alerts in a way that scales with tempo and avoids over-stimulation. A severity–confidence policy ensures that low-severity or low-certainty indications remain unobtrusive, while high-certainty, high-severity cases cut through the noise. Grouping alerts that occur in close succession prevents cascades, rate-limiting suppresses repeated notifications from the same track, and dismissing an alert should automatically generate an audit trail entry clarifying why it was disregarded. These elements help maintain trust and ensure operators focus on the most consequential developments.

Managing the operator's workflow is equally important. Interfaces that allow single-action cross-cueing—where selecting a track automatically directs a camera or opens the relevant sensor panel—remove friction and reduce time spent on mechanical manipulation rather than decision-making. Presenting an inline evidence bundle that aggregates sensor snapshots, RF identifiers, and recent motion cues avoids disjointed tab-switching and brings all validation-relevant information to one place. An escalation drawer with pre-filled messages or structured handover templates enables rapid coordination with external actors during time-critical events.

During dense or complex scenes, adaptive display behaviour prevents overload. Interfaces that automatically cluster low-priority tracks, elevate critical ones visually, and allow the operator to enter a "focus mode" centred on a single high-impact target maintain situational clarity, ensuring that even when the scene becomes busy, cognitive load remains manageable.

Finally, robust recording and forensic functionality underpin both accountability and continuous improvement. Native-resolution capture of sensor feeds, combined with a synchronized event timeline showing system and operator actions, creates an authoritative record. The ability to replay incidents with aligned sensor panels enables detailed review, supporting both training and system refinement.

As a whole, these principles point toward HMIs that surface essential information with minimal friction, compress the time between perception and action, and maintain clarity in high-tempo, high-density operations.

LESSONS LEARNED FROM OPERATIONAL SYSTEMS AND TEST METHODOLOGIES

This section consolidates recurring interface insights observed across multi-vendor C–UAS evaluations, focusing on how information was presented, how operators acted on it, and which design choices consistently shortened time-to-understanding and time-to-action. Alerts were most effective when they encoded both severity and confidence in a visible, consistent manner, so that low-severity or low-confidence indications remained unobtrusive while high-priority items cut through the noise. Rate-limiting and grouping proved essential to avoid alert cascades; clustering notifications by track and suppressing rapid repeats prevented cognitive spikes and preserved attention for the most consequential events. Alerts that were immediately actionable—arriving with one-click controls to direct a camera, verify a classification, or escalate to the right authority—shortened decision chains and reduced hand–eye travel.

Several visualization patterns supported quick comprehension under time pressure. Operators benefited from persistent, glanceable cues for track recency and quality, reducing the risk of relying on stale or low-confidence data. Predictive overlays such as short-horizon trajectory cones and arrival bands shifted behaviour from chasing to anticipating targets. Uncertainty worked best when it was explicit on the primary view: position ellipses or heat halos and simple confidence badges were easier to interpret than hidden numeric fields. A compact but consistent symbology, with stable colours and shapes for states and actions, reduced misreads during load peaks and smoothed handovers between team members.

Cross-cueing and evidence consolidation had clear, measurable impact. Single-action cross-cueing—selecting a track and immediately tracking EO/IR while opening a compact sensor panel—removed friction and protected scarce seconds in high-tempo moments. Inline evidence bundles that collocated the most recent EO/IR frame, a short track-history strip, and RF/ID hints reduced tab-hopping and contradictory interpretations, enabling quicker and more confident verification. When automated reclassifications were accompanied by a short rationale showing which sensor contributions or features drove the change, operators calibrated trust more accurately and second-guessed less.

Workflow design was strongest when surfaces and shortcuts were optimised for the dominant path from validate to classify to decide. Burying key controls in secondary menus introduced avoidable delays, whereas keeping a focus mode one gesture away reduced cognitive switching by temporarily filtering the scene to the highest-priority track. Keyboard parity with mouse interactions—hotkeys for acknowledge, track, toggle-timeline, and escalate—kept pace under pressure and reduced the risk of interaction slips when fine pointer control was difficult.

Lightweight temporal context further stabilised sense-making. An always-on micro-timeline per track, rendered as a narrow sparkline of detections, drops, and re-acquisitions, helped operators rapidly reconstruct what just happened after interruptions. Near-real-time replay with a 15–30s look-back window proved useful beyond post-mortem analysis; it helped catch near-misses, recover association after occlusions, and support quick cross-checks without leaving the main display.

Managing density and information load on the primary view remained critical. A practical three-tier information architecture, with map and alerts as the persistent core, on-demand sensor panels and timeline as the working layer, and logs and reports in a tertiary layer, kept essential cues visible while preserving access to depth. Within that frame, small hover-expandable cards outperformed large pop-ups by preserving spatial context and avoiding occlusion of adjacent tracks or geofences.

Environmental robustness at the UI layer reduced needless searching and improved interpretation of sensor behaviour. Compact widgets near the map for wind, visibility, and RF congestion helped operators understand dropouts or degraded confidence without hunting through diagnostic tabs. During multi-track surges, auto-degradation that clustered low-priority objects, stabilised labels for top threats, and suppressed nonessential adornments reduced attention thrash and maintained continuity of the task.

Operator feedback and readiness features inside the HMI paid dividends. A handful of embedded practice vignettes, triggered on demand, exposed UI pitfalls before live operations and reduced on-shift surprises. Subtle micro-prompts—short contextual hints such as auto-tracking armed or track recently stale—guided newer operators without slowing experienced users and created a common baseline of status awareness across shifts.

To keep assessments centred on interaction quality rather than sensor physics, a small set of HMI-focused indicators proved discriminative in trials and bench tests alike. Time-to-Alert Acknowledgement measures the delay from alert onset to the operator's acknowledgement; Time-to-Camera-Tracking captures the interval from track selection to a sensor-on-target view; and Time-to-Verification measures the path from the initial alert to a verified benign or threat decision. The False Alarm Rate quantifies how well the interface and policy prevents overload. UI continuity under load monitors the number of concurrent tracks the system can handle before interaction latencies exceeded a threshold. Together, these measures tie interface behaviour to operator outcomes, making it possible to evaluate and iterate HMIs with the same discipline typically reserved for sensing performance.

The discussion above leads to the following actionable design checklist for C-UAS HMIs:

1. Alerts encode severity and confidence, with grouping and rate-limit policies.
2. Track cards show freshness, uncertainty, and last-seen on the map, not in a subview.
3. One-action cross-cueing (select → camera on target) is guaranteed.
4. Inline evidence bundle (map + EO/IR frame + RF/ID + timeline) accompanies every high-priority alert.
5. Focus mode and replay (last 15–30s) are one gesture away.
6. Hotkeys exist for acknowledge, track, verify, escalate; mouse parity is preserved.
7. UI auto-clusters low-priority tracks and stabilizes labels for top threats under load.
8. Environmental context (wind/visibility/RF congestion) is always visible near the map.

These lessons emphasize that operator performance hinges less on raw sensor range and more on how the interface surfaces uncertainty, compresses actions, and stabilizes attention when the scene becomes busy.

CONCLUSIONS

This paper examined the role of human--machine interfaces in counter–UAS operations and identified interaction patterns that most strongly influence operator performance. Modern C–UAS systems can only reach their full potential when the interface supports rapid comprehension, transparent uncertainty, and efficient action under time pressure. Across the analysis, a recurring theme emerged: technical sensor performance is necessary, but not sufficient. Operational effectiveness ultimately depends on how clearly and reliably information is surfaced to the human operator, especially during periods of high workload or ambiguous sensor cues.

The lessons learned show that several design elements consistently accelerate operator understanding and reduce errors: explicit visualization of data freshness and uncertainty, one-action cross-cueing between sensors, compact evidence bundles for rapid verification, structured alert prioritization, and adaptive displays that automatically manage clutter during load spikes. Interfaces implementing these principles enabled operators to stay ahead of the scenario rather than being forced into reactive behaviour. Conversely, systems that buried critical signals, obscured uncertainty, or fragmented information across multiple windows imposed unnecessary cognitive costs.

Another major insight is that evaluations of C–UAS performance must foreground HMI behaviour, not treat it as secondary. Ultimately, the effectiveness of future C–UAS systems will depend on interfaces that let operators understand evolving airspace situations at a glance, act with confidence, and maintain situational control even in fast-moving, uncertain conditions. Continued research into adaptive visualization, uncertainty communication, cognitive ergonomics, and collaborative interaction will be essential for bridging the gap between technical capability and real-world performance.

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