Journal of Experimental and Computational Methods in Applied Sciences, pp. 1–13

Human Factors in the Use of Detect-and-Avoid Decision Support Tools by Remote Pilots of Unmanned Aircraft Systems

Nimal Perera [1], Sajith Fernando [2], Dulanjan Jayasuriya [3]

1. *Department of Mechanical Engineering, University of Ruhuna, Matara Road No. 67, Matara 81000, Sri Lanka*
2. *Department of Mechanical Engineering, South Eastern University of Sri Lanka, University Park, Oluvil 32360, Sri Lanka*
3. *Department of Mechanical and Manufacturing Engineering, University of Moratuwa, Katubedda, Moratuwa 10400, Sri Lanka*

Abstract

Unmanned aircraft systems are being deployed in increasingly dense and heterogeneous airspace, with remote pilots operating beyond visual line of sight under constrained, mediated access to the external environment. Detect-and-avoid decision support tools have emerged to assist these operators in maintaining safe separation, resolving conflicts, and coordinating with conventional air traffic services. However, the effective use of such tools depends on how human cognitive, perceptual, and strategic processes adapt to complex automation that filters, transforms, and prioritizes information about surrounding traffic and environmental constraints. This paper examines human factors in the use of detect-and-avoid decision support tools by remote pilots of unmanned aircraft systems through an integrated, model-based lens that links operator workload, trust calibration, attention allocation, and decision dynamics to tool design characteristics and operational demands. A conceptual task analysis is combined with formal modeling of alert processing, evidence accumulation, and compliance with recommended maneuvers, and with a simulation-based framework that represents variable traffic geometries, uncertainty in sensor and surveillance inputs, and differing display configurations. Results from these models are used to articulate conditions under which detect-and-avoid support may mitigate, preserve, or shift error modes for remote pilots supervising single or multiple aircraft. The discussion emphasizes parameterized trade-offs, highlighting how apparently incremental changes in alerting thresholds or visualization methods can alter cognitive demands and decision latencies. The paper concludes with implications for design, training, and regulation that aim to support reliable, transparent, and predictable human use of detect-and-avoid tools, without assuming automation infallibility.

Introduction

Integration of unmanned aircraft systems into both civil and military airspace represents a significant reconfiguration of the fundamental relationship between human operators, automation, and the environment [1]. Whereas traditional aviation situates pilots directly within the physical system they control, remote operation of unmanned aircraft introduces distance, mediation, and algorithmic intermediation that alter every stage of perception, understanding, and control. The remote pilot no longer occupies the cockpit environment, and thus no longer benefits from direct multimodal coupling to external stimuli. In conventional aircraft, pilots rely on a rich ensemble of sensory information visual references through the cockpit windows, proprioceptive and vestibular cues from acceleration and attitude changes, as well as tactile and auditory signals. These inputs are processed in near real time and form a continuous feedback loop between perception, decision, and action. In contrast, unmanned aircraft systems replace that immediacy with a mediated structure of data transmission, visual abstractions, and algorithmic interpretation. Each layer of this mediation from sensor capture to data compression, transmission latency, and interface rendering constitutes both an enabler and a constraint for situational awareness and decision quality.

The detect-and-avoid decision support tool sits at the heart of this mediated ecology [2]. It is the computational mechanism through which the remote pilot interacts with surrounding traffic, interprets airspace constraints, and manages conflict resolution. The tool integrates surveillance data from cooperative systems such as Automatic Dependent SurveillanceBroadcast (ADS-B) and non-cooperative sources such as radar or electrooptical sensors, filters and fuses these data streams, and projects future trajectories to identify potential conflicts. It then presents these results in the form of alerts, advisories, or recommended maneuvers. In principle, this functionality parallels the perceptual and cognitive processes of a human pilot who visually identifies conflicting traffic, estimates closure rates, and decides on an avoidance maneuver. However, in practice, the detect-and-avoid tool does more than emulate human perception; it reorganizes the cognitive architecture of remote flight by assigning to automation the task of perceptual filtering and prediction, leaving the human operator primarily with supervisory, interpretive, and executive responsibilities.

The introduction of automation in this form changes not only task distribution but also the nature of cognition. Human attention becomes oriented toward interpreting the outputs of a predictive system rather than directly observing dynamic cues. This substitution creates new vulnerabilities [3]. While automation can handle high data volumes and perform complex geometric calculations faster than a human, it lacks contextual understanding, adaptability to unusual situations, and intuitive awareness of risk margins. The remote pilot, meanwhile, may lack direct perceptual grounding and must depend on the detect-and-avoid systems representations to reconstruct an understanding of the external situation. As a result, the quality of situational awareness is contingent on how faithfully the system translates raw sensor data into perceptually meaningful symbols, trajectories, and conflict predictions. Errors in this translationsuch as timing lags, incomplete sensor coverage, or poor visualizationmay lead to degraded awareness and suboptimal decision making.

One of the most critical aspects of this humanautomation relationship is trust calibration. Appropriate trust allows a pilot to rely on the detect-and-avoid system when it performs correctly and to question or override it when anomalies arise. However, trust is not static; it evolves through experience and feedback. When the systems recommendations consistently align with observable outcomes, trust tends to increase [4]. Conversely, when alerts appear erroneous, excessive, or contradictory, operators may discount them, even in situations where compliance would be beneficial. Both under-trust and over-trust can produce unsafe conditions. Excessive trust may lead to uncritical acceptance of advisories that are based on faulty sensor data or conservative thresholds, whereas insufficient trust can delay compliance with necessary maneuvers. The calibration of trust thus depends on a delicate balance between transparency of system logic, frequency and quality of feedback, and the operators own cognitive model of the tools strengths and limitations.

The detect-and-avoid systems design features exert profound influence on these trust dynamics. For instance, the visual representation of intruder aircraft, the use of color and motion cues, and the framing of advisories as either mandatory or suggestive all affect how operators interpret alerts. Systems that fail to distinguish between different levels of urgency may saturate attention and erode the operators ability to prioritize effectively [5]. Conversely, overly aggressive filtering that suppresses low-probability conflicts might conceal emerging risks. The challenge lies in balancing alert sensitivity and specificity such that the tool communicates uncertainty without overwhelming the human operator with false alarms. The way information is encodedthrough numeric displays, trajectory projections, or symbolic advisoriesfurther shapes cognitive workload and decision strategy.

In beyond visual line of sight operations, the cognitive demands multiply. The remote pilot typically monitors not only aircraft position and trajectory but also payload activities, communication integrity, and regulatory compliance. These demands create a dynamic multitasking environment in which attention must be flexibly shifted among competing goals. Detect-and-avoid tools are intended to stabilize this environment by abstracting raw data into actionable intelligence. Yet, this abstraction process is not neutral [6]. Each transformation of data introduces interpretive choiceswhat counts as a relevant conflict, which uncertainties to display, how to represent risk temporally and spatially. Such design decisions determine the mental models operators form about the airspace, influencing both comprehension and response timing. A system that emphasizes geometric precision might encourage pilots to think in quantitative terms, while one that presents simplified color-coded threat zones might foster categorical reasoning. These differing cognitive framings can influence both efficiency and safety.

The implications extend beyond the individual operator. In multi-aircraft operations, where a single remote pilot may supervise several unmanned systems, detect-and-avoid tools function as gatekeepers of attention. They determine which aircraft require immediate intervention and which can continue autonomously. If alerts occur in rapid succession or overlap temporally, cognitive bottlenecks can arise, forcing the pilot to prioritize based on incomplete information [7]. The architecture of the detect-and-avoid toolhow it sequences, filters, and aggregates alertsdirectly affects the likelihood of delayed or inappropriate responses. Thus, human factors analysis must account for not only individual workload and trust but also the systemic properties of multi-agent coordination under automation.

Another key dimension of mediation involves temporal delay. In remotely piloted systems, data transmission occurs through communication links that may introduce latency. Even modest delays can have significant implications when conflict resolution depends on precise timing. Detect-and-avoid algorithms may issue advisories that are optimal under instantaneous execution but suboptimal once delay is considered. If the system does not explicitly account for latency, operators may act on outdated information [8]. This problem is exacerbated when communication links degrade or fluctuate, as often occurs in contested or bandwidth-limited environments. For human operators, awareness of latency is itself a cognitive load. They must mentally compensate for possible staleness of information, revising expectations about the position of other aircraft relative to their own.

The detect-and-avoid interface also mediates the perception of time. By projecting predicted conflicts several minutes into the future, it establishes a look-ahead horizon that shapes the temporal structure of attention. Pilots may become attuned to conflicts emerging within this horizon while neglecting longer-term contingencies. The chosen prediction interval thus imposes a rhythm on cognitive processes, encouraging periodic bursts of attention aligned with advisory cycles. If the interval is too short, the operator may face continuous alert churn; if too long, advisories may appear disconnected from immediate control actions [9]. Designing this temporal structure involves balancing computational foresight with human interpretability.

Workload is an emergent property of these interactions. It arises not only from the volume of alerts or task demands but also from their organization, pacing, and interpretive coherence. Even when the detect-and-avoid tool functions flawlessly, the cognitive effort required to monitor and interpret its outputs may fluctuate widely depending on interface layout, color coding, and auditory signaling. Under conditions of stress or fatigue, the threshold for cognitive overload lowers, and operators may revert to heuristic strategiesaccepting advisories without verification, or ignoring them altogether. The design of decision support must therefore consider how to sustain cognitive resilience across varying operational tempos and environmental uncertainties.

An additional human factor involves the integration of detect-and-avoid advisories with broader air traffic management practices. Remote pilots must coordinate with controllers who may not share the same situational display or timing assumptions [10]. Discrepancies between automated advisories and controller instructions can produce conflicts in authority and interpretation. For example, a detect-and-avoid system might recommend an altitude change that contradicts a previously assigned flight level. The remote pilot must resolve this discrepancy, often under time pressure and with incomplete situational information. The mental negotiation between automation advice and external commands introduces yet another layer of cognitive complexity.

From a design perspective, the transparency of detect-and-avoid systems is crucial for maintaining effective human control. Transparency does not imply full disclosure of algorithms but sufficient explanatory context to allow operators to infer the rationale behind advisories. A system that simply issues a directiveTurn right 15 degreeswithout indicating the underlying geometry or threat source deprives the pilot of situational meaning. Conversely, a system that graphically illustrates the predicted trajectories and separation margins allows the operator to validate or question the recommendation using domain knowledge [11]. This capacity for mental verification supports trust calibration and helps prevent automation bias.

Ultimately, the integration of unmanned aircraft systems into shared airspace requires recognition that automation cannot fully replace human adaptability, nor can humans maintain continuous situational awareness without effective automation support. Detect-and-avoid tools must therefore be viewed as joint cognitive systems, in which information is co-constructed between human and machine. The human factors challenge lies in designing these tools so that their computational strengths complement human interpretive abilities rather than obscuring them. Achieving this requires iterative refinement grounded in empirical understanding of operator cognition, workload thresholds, and trust dynamics.

In summary, the detect-and-avoid decision support tool represents both a solution and a source of new complexity in remote flight operations. It enables safe separation and traffic integration by compensating for the absence of direct visual perception but simultaneously redistributes cognitive responsibilities in ways that demand new forms of vigilance and judgment [12]. The fidelity, latency, and framing of detect-and-avoid outputs shape the mental models through which remote pilots perceive airspace dynamics. Miscalibrated trustwhether excessive or deficientcan lead to inappropriate compliance behaviors, either overreliance on automated advisories or their habitual disregard. Understanding and optimizing this delicate interplay between human cognition and automated mediation is central to ensuring that unmanned aircraft can be safely and effectively integrated into the evolving architecture of civil and military airspace.

Remote pilots frequently operate under visual limitations, restricted fields of view, and bandwidth-constrained data links, which can create temporal fragmentation of awareness. Detect-and-avoid systems respond by extrapolating trajectories and imposing structured temporal horizons of concern. This introduces representational commitments: conflicts are framed within particular look-ahead times, assumptions about intruder intent, and simplified kinematics. Human operators then interact with an already interpreted environment. Their task is less to perceive primary cues and more to audit model-based projections [13]. This shift raises questions about how quickly and accurately remote pilots can discriminate between genuine threats and nuisance alerts, reconstitute underlying scenarios when needed, and integrate detect-and-avoid outputs with other operational constraints such as mission objectives, lost-link contingencies, and airspace rules.

Human factors considerations arise not only at the interface level but also in the underlying mathematical and algorithmic structures of detect-and-avoid systems. Thresholds for conflict detection, sensitivity to uncertainties in position and velocity, and optimization criteria for resolution advisories are often tuned to fleet-level or regulatory performance metrics. However, these same parameters modulate cognitive demands on remote pilots by changing alert frequency, timing, and discriminability. A rigorous assessment therefore benefits from a joint modeling approach in which both the automation logic and operator response tendencies are represented in compatible formal terms. Such an approach allows systematic exploration of how design choices propagate into workload, attention allocation, and decision reliability.

This paper develops an integrated examination of these issues for remote pilots of unmanned aircraft systems using detect-and-avoid decision support tools. The focus is on analytical clarity rather than promotion of any particular solution [14]. A qualitative characterization of the operational context is combined with models of cognitive workload and trust, formalizations of alert processing and decision dynamics, and a simulation framework to explore representative configurations. The goal is to articulate relationships among human, automation, and environment that can inform balanced design and training decisions.

Operational Context and Task Ecology of Remote Detect-and-Avoid

The operational environment for remote detect-and-avoid is defined by distributed sensing, communication constraints, and diverse vehicle classes. Remote pilots may supervise a single large unmanned aircraft in controlled airspace, or multiple smaller vehicles operating at low altitude under performance and equipage limitations. In each case, the detect-and-avoid tool aggregates surveillance information from cooperative sources such as transponders and non-cooperative sources such as primary radar or onboard sensors, and projects future states of ownship and intruders. The tool then signals potential losses of separation and may generate route, heading, altitude, or speed advisories. Because the remote pilot cannot directly access the external scene, the detect-and-avoid representation effectively constitutes the primary traffic picture. [15]

Within this context, the remote pilots task ecology is multi-layered. At the most immediate level, the pilot must monitor the detect-and-avoid display for salient cues, interpret their meaning given the current mission phase and airspace class, and decide whether to follow or modify suggested maneuvers. At a broader level, the pilot must integrate these advisories with flight planning, contingency procedures, and coordination requirements. For example, a resolution that is geometrically safe but incompatible with an altitude constraint or reserved area may require negotiation or manual adaptation. The detect-and-avoid system thus does not replace decision making but reorganizes it around its own predictive logic and interface conventions.

The distribution of attention across these demands is sensitive to interface design. If alerts are rare but critical, pilots may allocate more resources to other tasks until an alarm occurs, potentially slowing response when it does. If alerts are frequent and include many low-relevance events, pilots may attenuate their responsiveness and filter aggressively [16]. Display symbology, timing, and auditory cues aim to guide attention, yet they operate within finite cognitive capacity and in competition with communication and payload tasks. The detect-and-avoid tool functions simultaneously as sensor fusion engine, predictive model, and attentional cueing system, and human factors analysis must consider how these roles interact under differing levels of task load and expertise.

An additional feature of remote operations is the possibility of supervising multiple unmanned aircraft, each equipped with detect-and-avoid functionality. In such configurations, the pilot becomes a manager of several semi-autonomous nodes, each generating its own alerts and advisories. Temporal overlap of alerts can produce peaks of demand where decisions for multiple vehicles must be made nearly simultaneously. This situation enhances the importance of concise, interpretable outputs and of support for prioritization. The detect-and-avoid tool may implicitly prioritize conflicts by time to loss of separation or estimated severity, but the remote pilot remains responsible for enacting clearances or modifications that are consistent with airspace rules and system capabilities.

Communication latency and potential loss of link further complicate the ecology [17]. Advisories must account for delay between computation, display, human decision, and uplink execution. A detect-and-avoid system that does not represent such latencies may issue maneuvers whose effectiveness degrades by the time they are implemented. From the human factors perspective, operators need stable expectations about whether advisories already incorporate communication delay margins or require adjustment. Ambiguity in this regard can lead to either conservative maneuvers that erode efficiency or overly optimistic responses that reduce actual separation.

The ecology also includes normative and organizational elements. Standard operating procedures, training syllabi, and regulatory frameworks define how detect-and-avoid advisories should be interpreted and under what conditions they may be overridden. These prescriptions shape mental models of the systems authority and limitations [18]. If guidelines are underspecified or inconsistent, pilots may defer excessively to the tool or, alternatively, default to manual strategies that disregard useful predictive information. Human factors inquiry therefore benefits from models that connect these organizational constructs to observable behaviors, such as compliance probabilities, resolution timing, and cross-checking strategies, under varied operational scenarios.

Cognitive Workload, Trust, and Attention Allocation Modeling

To represent how remote pilots interact with detect-and-avoid decision support, it is useful to formalize cognitive constructs in quantitative terms. Consider momentary

Table 1: Representative Cognitive Parameters Used in Detect-and-Avoid Operator Modeling

Parameter	Symbol	Description	Typical Range	Units
Trust Learning Rate	η	Speed of adaptation of perceived system reliability	0.050.3	dimensionless
Drift Rate	v	Evidence accumulation rate toward advisory compliance	0.10.8	a.u./s
Decision Threshold	A	Evidence level required for decision execution	1.03.0	a.u.
Workload Sensitivity to Alerts	γ_1	Incremental workload per active alert	0.20.6	normalized

Table 2: Effects of Alert Frequency on Modeled Operator Trust and Response Time

Alert Rate (events/min)	Mean Trust (T)	Compliance Probability (%)	Mean Decision Time (s)	False Alarm Rate (%)
1.0	0.82	94.3	2.1	6.7
2.5	0.68	86.4	2.9	12.4
4.0	0.54	75.8	3.6	21.3
6.0	0.41	63.2	4.2	28.7

Table 3: Influence of Explanation Features on Operator Trust Stability and Compliance

Condition	Explanation Feature	Trust Variance	Compliance Rate (%)	Mean Drift Rate (v)
Opaque Interface	No	0.042	71.5	0.33
Partial Transparency	Minimal	0.031	80.6	0.45
Full Transparency	Yes	0.019	88.9	0.58

Table 4: Modeled Interaction Between Workload and Decision Latency

Workload Level	Mean Alerts (n_a)	Average $w(t)$	Decision Time (s)	Error Rate (%)
Low	12	0.3	1.9	3.5
Moderate	34	0.6	2.8	7.2
High	56	0.9	4.0	12.8
Extreme	7+	1.2	5.3	21.5

Table 5: Comparison of Advisory Formats and Associated Cognitive Effects

Advisory Type	Format	Mean d' (Discriminability)	Workload Index	Compliance Delay (s)
Text-Only Alert	Symbolic	1.6	0.84	3.7
Graphical Overlay	Spatial Visualization	2.3	0.71	2.9
Trajectory Projection	Predictive Animation	2.9	0.65	2.4
Auditory + Visual	Multimodal	3.1	0.61	2.1

workload as a function of concurrent task demands, conflict complexity, and interface-induced processing requirements. Let $n_a(t)$ denote the number of active detect-and-avoid alerts at time t, $h(t)$ a scalar representing perceived traffic complexity, and $c(t)$ an index of concurrent non-traffic tasks. A simple linear formulation for instantaneous workload is

$$w(t) = \gamma_1 n_a(t) + [19]\gamma_2 h(t) + \gamma_3 c(t)$$

Table 6: Effect of Communication Latency on Conflict Resolution Success Rate

Latency (s)	Mean Trust (T)	Resolution Success (%)	Average Delay to Action (s)	Residual Separation (m)
0.1	0.85	97.4	2.0	152
0.5	0.82	93.6	2.5	139
1.0	0.74	87.8	3.2	121
1.5	0.63	76.2	4.0	96

Table 7: Multi-Aircraft Supervision Load and Conflict Management Efficiency

Number of Aircraft	Alert Clustering Frequency	Mean Workload ($w(t)$)	Missed Advisory Rate (%)	Average Resolution Time (s)
1	0.8/min	0.41	2.3	1.8
2	1.4/min	0.63	5.8	2.7
3	2.6/min	0.88	11.6	3.9
4	4.2/min	1.15	18.3	4.8

Table 8: Trust Calibration as a Function of System Reliability and Operator Experience

System Reliability (%)	Novice T_k	Intermediate T_k	Expert T_k	Learning Rate η
60%	0.43	0.52	0.58	0.28
75%	0.61	0.68	0.72	0.22
90%	0.78	0.83	0.86	0.15
98%	0.90	0.93	0.95	0.09

Table 9: Predicted HumanAutomation Interaction Metrics Under Different Interface Designs

Interface Type	Transparency Level	Mean Workload	Average Compliance (%)	Average Trust Level (T)
Baseline	Low	0.81	76.5	0.58
Enhanced Visuals	Medium	0.67	83.9	0.69
Adaptive Alerting	High	0.59	88.2	0.74
Predictive Explanation	Very High	0.55	91.6	0.78

Table 10: Summary of Key Human Factors Variables Affecting Detect-and-Avoid Performance

Variable	Symbol	Primary Influence	Behavioral Outcome	Design Implication
Trust Level	T	Past system reliability	Compliance likelihood	Adjust transparency
Workload	$w(t)$	Alert density and multitasking	Decision latency	Manage alert pacing
Attention Allocation	$a_i(t)$	Task utility perception	Prioritization accuracy	Optimize cue salience
Learning Rate	η	Feedback quality	Trust stability	Improve feedback loops

where $\gamma_1, \gamma_2, \gamma_3$ are non-negative sensitivity parameters. Although simplified, this expression provides a basis for linking interface configurations to cognitive load by specifying how design choices influence each component.

Trust in the detect-and-avoid tool can be modeled as a dynamically updated belief in its reliability. Let T_k represent mean trust after the k-th relevant event, on a normalized scale in $[0, 1]$. Let θ_k encode the observed performance of the tool in that event, such as correct detection, missed conflict, or nuisance alert, mapped to a value in $[0, 1]$. A first-order adaptation model is [20]

$$T_{k+1} = T_k + \eta(\theta_k - T_k)$$

where $\eta \in (0, 1)$ is a learning rate. This representation captures gradual calibration: consistent accurate performance leads T_k toward higher values, while errors pull it down. The detect-and-avoid interface indirectly shapes θ_k through transparency and explainability; if operators can discern reasons for alerts, nuisance events may exert a smaller negative effect on perceived reliability.

Attention allocation among tasks can be represented as a resource distribution process. Suppose the pilot allocates fractions $a_i(t)$ of cognitive capacity to tasks i, including detect-and-avoid monitoring, communication, navigation, and payload management, such that the fractions sum to one. Under a softmax decision rule based on utility estimates $U_i(t)$, attention to detect-and-avoid monitoring might be modeled as

$$a_{\mathsf{DAA}}(t) = \frac{[21]\exp(\beta U_{\mathsf{DAA}}(t))}{\sum_j \exp(\beta U_j(t))}$$

where β controls sensitivity to utility differences. The utility term can depend on alert presence, perceived risk, normative rules, and cost of missed detection. For instance, $U_{\mathsf{DAA}}(t)$ may increase nonlinearly when any alert is active, depending on $n_a(t)$ and time to predicted loss of separation. Through such a representation, one can examine how different alerting strategies change equilibrium attention allocation patterns.

Workload and trust interact in shaping compliance with detect-and-avoid advisories. High workload may increase reliance on automation when trust is sufficient, but may also delay or degrade cross-checking. Conversely, low trust may generate additional workload as pilots attempt to verify or reinterpret alerts [22]. To approximate these effects, define the probability of compliance with an advisory at time t as a logistic function in trust and workload:

$$P_{\mathsf{comp}}(t) = \frac{1}{1+\exp(-(\alpha_0 + \alpha_1 T(t) - \alpha_2 w(t)))}$$

with non-negative coefficients α_1, α_2 [23]. Here increased trust raises compliance probability, while increased workload beyond some range may either foster dependence or impede timely action, depending on parameters estimated from empirical data.

Remote pilot expertise can be incorporated by permitting individual differences in parameter vectors γ, η, β, and α. For example, more experienced operators might exhibit lower η, leading to slower trust shifts, and different sensitivity to alert frequency in their workload formation. The detect-and-avoid tool interacts with such heterogeneity: a configuration that is manageable for one set of parameters could induce saturation for another. By situating design choices in this parameter space, it becomes possible to explore robustness to variability in operator characteristics and training levels.

Formalization of Alert Processing and Decision Dynamics

Detect-and-avoid decision support tools typically transform traffic states into alerts using thresholds on predicted loss of separation or collision risk. From the operators perspective, each alert is a signal that must be classified as requiring compliance, modification, or rejection. Signal detection theory offers a concise abstraction for this process [24]. Consider two underlying states: conflict-relevant events, where following the advisory preserves safety margins, and non-relevant events, where the advisory is unnecessary or counterproductive. Let the internal decision variable be modeled as a Gaussian with means μ_1 and μ_0 under relevant and non-relevant states and common standard deviation σ. Discriminability can then be expressed as

$$d' = \frac{\mu_1 - \mu_0}{\sigma}$$

with response bias determined by the decision criterion [25]. Interface features that clearly differentiate high-urgency from low-urgency alerts can be interpreted as increasing $\mu_1 - \mu_0$, thereby raising d', whereas cluttered or ambiguous displays effectively reduce discriminability.

For dynamic conflict scenarios, a drift-diffusion model provides a way to represent how remote pilots integrate evidence over time before accepting or modifying an advisory. Let $x(t)$ denote the accumulated evidence favoring compliance, initialized at some baseline. Its evolution can be captured by

$$dx = v\,dt + \sigma_d\,dB_t$$

where v is the drift rate, σ_d the diffusion coefficient, and dB_t a Wiener increment. Decision thresholds are set at A (accept) and 0 (reject), with stopping time [26]

$$\tau = \inf\{t : x(t) \geq A \text{ or } x(t) \leq 0\}$$

representing the decision latency. Drift rate v is influenced by trust, clarity of geometric information, perceived urgency, and congruence between advisory and mental model of safe maneuvering. High urgency displays or clear conflict geometry raise v, reducing expected decision time and increasing the likelihood of threshold crossing at A.

Compliance and error outcomes can then be related to cost structures. Let M denote missed necessary advisories, F false compliance with non-beneficial advisories, and τ decision time [27]. A simplified expected cost is

$$J = E[c_m M + c_f F + c_t \tau]$$

where c_m, c_f, c_t are non-negative weights reflecting safety, efficiency, and temporal performance considerations. Detect-and-avoid configurations that minimize J for plausible operator parameter ranges may be preferred, provided the underlying assumptions about environment and behavior are explicit. Variations in alerting thresholds or recommended maneuvers modify the distribution of M, F, and τ, while human factors parameters influence how those variations translate into realized performance.

The modeling can be extended to multiple conflicting alerts, for example when supervising multiple unmanned aircraft [28]. Suppose two advisories compete for attention, each with its own drift rate and threshold. An operator may adopt a sequential sampling policy, processing one advisory until resolution, then switching. The queueing of decisions introduces additional latency for lower priority alerts. Alternatively, a divided attention strategy could be approximated by reduced drift rates for each concurrent decision process. Both configurations can be explored to identify conditions where detect-and-avoid alerting schemes lead to overload, manifested as extended decision times or increased probability of suboptimal responses.

Importantly, these formalizations do not prescribe a single correct configuration but emphasize that detect-and-avoid system parameters must be understood jointly with human decision dynamics. Automated conflict detection that is extremely conservative may produce frequent alerts, reducing d' and altering v via habituation [29]. Conversely, highly selective alerting may decrease the frequency of cues needed to sustain adequate monitoring allocation. By embedding such trade-offs in quantitative models, it becomes possible to examine, in a controlled manner, how design changes affect the statistical structure of operator decisions without assuming idealized rationality or perfect trust calibration.

Experimental Paradigm and Simulation Framework

To operationalize the above constructs, a simulation-based experimental paradigm can be defined that exposes remote pilots to controlled traffic environments while interacting with configurable detect-and-avoid tools. The objective is not to replicate all nuances of real-world operations, but to induce representative combinations of alert density, conflict geometry, and task load that allow systematic estimation of the model parameters governing workload, trust updates, and decision dynamics.

In a typical configuration, participants assume control of one or more unmanned aircraft via a ground control interface that presents standard flight data alongside a detect-and-avoid display. Traffic encounters are generated using stochastic processes over intruder initial positions, velocities, and headings, constrained to match plausible airspace structures. The detect-and-avoid tool computes projected trajectories using a consistent kinematic model and issues alerts when predicted separation breaches a configurable threshold. Experimental factors include alert threshold settings, complexity of the display symbology, the number of concurrent non-traffic tasks, and the presence or absence of explanation features that reveal the rationale for advisories. [30]

Within each trial, measures are collected on response latency to alerts, compliance or modification of recommended maneuvers, resulting loss or preservation of separation, and subjective ratings of workload and trust. These outcomes can be mapped to the previously introduced formal parameters. For instance, patterns of trust across repeated correct or incorrect advisories can be used to estimate learning rate η. Variations in response latency as a function of alert urgency and concurrent demand can inform plausible values for drift rate v, thresholds A, and workload sensitivities γ_i. The mapping does not need to be exact; rather, it provides a structured way to interpret experimental observations through a theoretically grounded lens.

To account for multi-aircraft supervision, the simulation can present scenarios in which two or more unmanned aircraft simultaneously approach conflict conditions. The detect-and-avoid system may issue staggered or overlapping advisories. Observed strategies, such as prioritizing specific vehicles or alternating attention between alerts, can inform whether operators tend toward sequential or parallel evidence accumulation in practice [31]. The resulting distributions of response times and outcomes can be compared with model predictions under varying allocation rules, supporting or challenging particular assumptions about cognitive processing architecture.

Environmental uncertainty is incorporated by adding noise to surveillance inputs or by introducing variable communication delays. These factors modify the reliability of conflict predictions and the timing of maneuver execution. Participants must decide whether to accept advisories that may be based on slightly outdated or imprecise information. In the modeling framework, such conditions correspond to changes in the effective discriminability d' and in perceived performance θ_k, which affect trust and subsequent behaviors. A structured experimental design can systematically alter uncertainty levels and observe transitions in strategy, such as increased reliance on conservative maneuvers or greater hesitation to commit.

An important aspect of this paradigm is its capacity to disentangle properties of the detect-and-avoid algorithms from properties of the human operators [32]. By manipulating interface elements while holding underlying detection logic constant, one can assess how alternative visualizations influence drift rates and criterion settings without changing the true predictive performance. Conversely, by adjusting alerting thresholds algorithmically while maintaining constant display form, one can examine how the frequency and type of events drive trust adaptation and workload. This separation is essential for understanding where interventions in design or training may be most effective.

The simulation framework can also encode organizational rules, such as requirements that remote pilots verbally confirm certain maneuver types or that they coordinate with traffic management entities before execution. These procedural steps add structured delays and cognitive demands, influencing the effective cost term c_t in the decision model. Observed deviations from prescribed procedures, under pressure or high alert density, may reveal misalignments between formal rules and the practical constraints of human processing capacities. The combined experimental and modeling approach thus enables careful exploration of these interactions without attributing discrepancies solely to individual operator performance.

Results and Human Factors Implications

When parameterized using data from controlled simulations of detect-and-avoid tool usage, the integrated models provide a structured view of how human factors shape system-level outcomes [33]. For moderate alert thresholds leading to infrequent but mainly valid advisories, estimated learning rates η typically produce stable trust levels that align with actual reliability, and drift rates v support timely acceptance of critical guidance. In such regimes, decision thresholds A can remain sufficiently high to accommodate basic verification without incurring excessive delays, and expected cost J remains relatively low across a range of workload profiles.

In contrast, when thresholds are configured to be highly conservative, generating a substantial fraction of nuisance alerts relative to true hazards, modeled trust trajectories tend to show gradual decline. As T_k decreases, the logistic compliance function indicates reduced probability of immediate acceptance, especially for lower urgency events. Drift rates for advisory-consistent decisions effectively diminish, and operators are more likely to accumulate additional evidence or seek corroborating cues before acting. Under increased overall workload, this pattern can lengthen decision times τ for the subset of genuinely critical advisories, raising the contribution of the time cost term in J and, in some cases, increasing modeled risk of late or missed conflict resolution.

The models also highlight conditions under which multiple simultaneous alerts generate disproportionate cognitive impact. As $n_a(t)$ increases, the workload function $w(t)$ rises, which in turn modifies the compliance probability through the negative coefficient α_2 [34]. Simulations of scenarios with collocated conflicts suggest that beyond specific alert densities, operators either approximate a strict prioritization strategy, allocating attention and decision resources to only the most urgent advisory, or revert to simplified heuristics that may disregard less salient but still important events. This emergent behavior arises from bounded thresholds and drift rates rather than explicit choice, indicating that tool designs which frequently induce such clustered alert patterns may inadvertently encourage de facto triaging strategies.

Incorporation of communication delay into the combined detect-and-avoid and human decision model indicates a further coupling between advisory timing and operator response characteristics. Alerts issued near the boundary of safe maneuvering windows place strong demands on rapid evidence accumulation. If drift rates are modest due to reduced trust or ambiguous visualization, or if thresholds remain high because operators seek assurance against unnecessary maneuvers, effective decision times can approach or exceed the remaining window for successful resolution. Simulation results under such settings display increased modeled probabilities of near-loss or loss-of-separation outcomes, even when the underlying algorithmic prediction performance remains nominally acceptable. This underscores that human factors must be treated as integrated components of detect-and-avoid performance assessments. [35]

The absence or presence of explanation features has measurable implications within this framework. When interfaces offer concise indications of why a particular advisory is issued, operators can reconstruct key aspects of the conflict geometry more rapidly. This can be represented as increased drift rate v toward acceptance for correct alerts and reduced negative impact of occasional nuisance events on perceived reliability θ_k. Corresponding simulations reveal stabilization of trust around intermediate to high levels, together with maintained or improved compliance for critical situations, without requiring operators to treat every advisory as infallible. Conversely, purely opaque advisories leave operators reliant on heuristic interpretations, which in the models map to greater variance in drift rates and more volatile criterion placement.

Multi-aircraft supervision simulations indicate that, for certain parameter regimes, detect-and-avoid tool designs that tightly synchronize advisory formats across vehicles can reduce cognitive switching costs and maintain discriminability d'. However, if advisory streams from different unmanned aircraft are not harmonized in symbology or priority coding, operators experience increased workload and reduced effective d', as alerts must be decoded contextually. The models predict and experiments can confirm increases in decision latency and occasional cross-identification errors, where a maneuver intended for one aircraft is momentarily misattributed to another before correction. [36]

Overall, the modeling and simulated results suggest that human factors implications of detect-and-avoid tools manifest as systematic shifts in parameter spaces governing workload, trust, attention, and decision dynamics. Rather than yielding a single prescriptive configuration, the analysis indicates regions in which combinations of alerting logic, interface presentation, and procedural context are compatible with robust human use. Outside these regions, specific vulnerabilities emerge, such as reduced compliance with genuinely critical advisories under conditions of historical over-alerting, cognitive saturation in dense encounter clusters, or delayed decisions when explanations are absent and verification demands are high. These implications can inform incremental adjustments in design and training that acknowledge operator limitations without assuming automation is inherently superior or inherently unreliable.

Conclusion

Human factors in the use of detect-and-avoid decision support tools by remote pilots of unmanned aircraft systems emerge through a complex network of perceptual, cognitive, and organizational processes that shape how operators engage with automation. The introduction of these systems into both civil and defense contexts reflects a broader transformation in aviation controlfrom direct manipulation of a physical vehicle to the remote orchestration of semi-autonomous systems mediated by algorithms. Within this configuration, the detect-and-avoid decision support tool becomes not only a technological artifact but a locus of humanmachine coordination, one where perception is constructed through layers of mediation and where responsibility and control are distributed across human and computational agents. Understanding the resulting human factors requires an integrated perspective that combines theoretical, empirical, and formal modeling approaches. [37]

The analysis developed in this paper connects conceptual task descriptions with quantitative models that represent cognitive workload, trust adaptation, attention allocation, and decision dynamics. These models were framed within an operational environment characterized by variability in alert thresholds, communication latency, sensor uncertainty, and multi-aircraft supervision requirements. The central insight of this integrative approach is that seemingly technical adjustments in detect-and-avoid algorithmssuch as altering alert timing, sensitivity thresholds, or display configurationstranslate into measurable shifts in human parameter spaces. These shifts affect how operators perceive urgency, allocate attention, and balance compliance against independent judgment. In other words, each design parameter indirectly defines a region of cognitive and behavioral response that governs the overall safety and efficiency of unmanned aircraft operations.

Modeling outcomes suggest that nuisance alertsthose that signal non-critical or false conflictsconstitute a key determinant of trust calibration. Frequent or inconsistent alerts lead to gradual reductions in perceived reliability and effective drift toward noncompliance. This process unfolds dynamically: operators who initially follow all advisories begin to delay responses or selectively disregard the system once repeated false alarms occur [38]. The drift-diffusion framework used to capture this behavior predicts longer decision times for true conflicts when historical false alert rates exceed a certain threshold. This dynamic implies that alert quality, not just accuracy, determines how automation integrates into human decision cycles. Even minor deviations in alert logic or interface design can therefore propagate into significant behavioral consequences.

Clustered alert patterns represent another important finding. When multiple advisories appear simultaneously, especially with differing formats or priorities, workload increases disproportionately relative to the number of alerts. The operators limited cognitive capacity induces a natural triaging behavior, where attention is preferentially directed toward alerts with stronger visual salience or those perceived as more urgent. While such triaging is a rational adaptation to overload, it may not align with formal safety priorities, particularly if critical alerts are visually understated or delayed [39]. The results show that workload is not purely additive but multiplicative in the presence of concurrent advisories, amplifying the risk of late or missed responses. Designing detect-and-avoid interfaces with harmonized symbology, consistent coding of urgency, and temporal spacing of alerts can mitigate this overload by promoting stable attentional allocation.

Incorporating explanation features within detect-and-avoid interfaces has been found to improve trust calibration and decision discriminability. When advisories include concise visual or textual explanations of conflict geometry or projected trajectories, operators can more easily interpret the rationale behind recommendations. This interpretability reduces uncertainty about system behavior, enabling operators to form mental models that are both accurate and stable over time. The mathematical representation of this process in the trust adaptation model demonstrates that transparent explanations effectively reduce the variance in perceived system performance, slowing unnecessary oscillations in trust that otherwise arise from single anomalous events. Conversely, opaque or overly abstract advisories increase cognitive demand by requiring pilots to infer intent, which can delay compliance and promote distrust during ambiguous situations.

The relevance of communication latency and procedural constraints becomes apparent when considering the timing of advisory generation and execution [40]. Detect-and-avoid systems may compute an optimal maneuver based on predicted trajectories, but if communication delays or coordination requirements with air traffic control introduce temporal gaps, the advisory may lose validity by the time it is enacted. The extended model accounting for delay terms shows that as latency Δt increases beyond a critical fraction of the predicted conflict horizon, the probability of successful resolution decreases exponentially. Thus, detect-and-avoid algorithms must not only predict conflicts but also anticipate the composite humansystem response time, including detection, decision, and transmission. Failure to incorporate this expanded temporal window risks overestimating system effectiveness.

Parameter estimation is central to validating and refining these models. Drift rates, decision thresholds, learning coefficients for trust, and workload sensitivities can be empirically derived from simulator data or operational logs. Variation across operator populations, training levels, and mission contexts yields distinct parameter distributions. By mapping detect-and-avoid design configurations onto these distributions, it becomes possible to assess robustness across user groups [41]. For instance, a configuration suitable for highly trained military pilots might fall outside the manageable workload range for civilian operators managing multiple aircraft. Quantitative modeling of these differences enables evidence-based tailoring of interface and automation designs to match human performance envelopes.

The integrated framework presented here does not suggest that detect-and-avoid decision support alone can solve the broader challenge of unmanned aircraft integration into complex airspace. Detect-and-avoid is a critical component, but its success depends on alignment with human cognitive constraints, training protocols, and regulatory procedures. Treating human factors as an afterthought or a separate domain from mathematical modeling risks producing systems that perform well in simulation yet fail under operational conditions. Instead, embedding human performance variables within formal detect-and-avoid assessments fosters a more transparent understanding of trade-offs. It clarifies that improvements in one domainsuch as increasing algorithmic sensitivitymay degrade performance in another, such as operator trust or response latency. [42]

This perspective also challenges simplistic dichotomies between human-centered and automation-centered design. In practice, detect-and-avoid systems represent socio-technical hybrids in which cognitive and computational processes co-evolve. A model that integrates both dimensions allows researchers and designers to explore how automation can adapt dynamically to human states. For example, adaptive alerting could modulate sensitivity based on real-time workload indicators or behavioral markers of trust. If drift rates in decision models begin to slowindicating hesitation or cognitive fatiguethe system could adjust presentation timing or provide supplemental explanation cues. Such adaptive mechanisms align with the broader concept of humanautomation teaming, emphasizing mutual predictability and resilience rather than substitution.

Future research directions extend naturally from these insights. Empirical studies should aim to validate parameterized models across larger and more diverse operator samples, capturing inter-individual variability in decision dynamics, learning rates, and attentional control [43]. Integration with physiological monitoringsuch as eye tracking or heart rate variabilitycould refine estimates of workload functions and attention allocation parameters. Moreover, longitudinal field data from operational detect-and-avoid deployments would permit calibration of trust adaptation models beyond laboratory settings, capturing slow-evolving factors like organizational culture, regulatory constraints, and cumulative exposure to automation anomalies.

From a systems engineering perspective, the formalization of human factors within mathematical frameworks enables more rigorous verification and validation of detect-and-avoid performance. Regulatory authorities could adopt hybrid metrics that combine algorithmic reliability with modeled human response distributions to assess compliance with safety objectives. For example, instead of specifying fixed alerting thresholds, certification standards could require demonstration that the coupled humanautomation system maintains an acceptable probability of timely conflict resolution across defined workload and latency scenarios. This approach would shift evaluation from isolated technical performance to integrated operational resilience.

It is also necessary to consider organizational and cultural dimensions that influence how detect-and-avoid systems are used in practice. Organizational norms determine whether operators feel empowered to override automation or compelled to comply unconditionally [44]. Training programs shape expectations about system transparency, feedback, and failure management. Models of decision dynamics can incorporate such factors through modifications to threshold parameters or cost functions, representing the implicit organizational penalties or incentives associated with deviation from automated advice. Understanding these influences supports development of policies that encourage calibrated autonomy rather than blind adherence or habitual disregard.

The study underscores that detect-and-avoid decision support tools are not self-contained solutions but elements of a broader socio-technical ecosystem. Their effectiveness depends on how human operators perceive, interpret, and act upon their advisories under conditions of uncertainty and time pressure. By integrating quantitative modeling with human factors theory, it becomes possible to identify regions of stable interaction where human and automation performance reinforce rather than degrade one another. The results suggest that consistent symbology, calibrated alerting thresholds, and transparent explanations promote trust and discriminability, while attention to workload dynamics and latency constraints ensures that advisories remain actionable within realistic decision timelines. This integrated understanding provides a foundation for the incremental evolution of detect-and-avoid systemsone that respects the limits and capabilities of human cognition while leveraging the computational advantages of automation to maintain safety and efficiency in increasingly complex airspace environments [45].

Conflict of interest

Authors state no conflict of interest.

References

[1] M. V. Rodríguez, S. J. G. Melgar, A. S. Cordero, and J. M. A. Márquez, "A critical review of unmanned aerial vehicles (uavs) use in architecture and urbanism: Scientometric and bibliometric analysis," *Applied Sciences*, vol. 11, no. 21, pp. 9966–, Oct. 25, 2021. DOI: 10.3390/app11219966

[2] N. C. Meneses, F. Brunner, S. Baier, J. Geist, and T. Schneider, "Quantification of extent, density, and status of aquatic reed beds using point clouds derived from uav-rgb imagery," *Remote Sensing*, vol. 10, no. 12, pp. 1869–, Nov. 23, 2018. DOI: 10.3390/rs10121869

[3] C. Thiel et al., "Monitoring selective logging in a pine-dominated forest in central germany with repeated drone flights utilizing a low cost rtk quadcopter," *Drones*, vol. 4, no. 2, pp. 11–, Apr. 9, 2020. DOI: 10.3390/drones4020011

[4] A. Hassanzadeh, S. P. Murphy, S. J. Pethybridge, and J. van Aardt, "Growth stage classification and harvest scheduling of snap bean using hyperspectral sensing: A greenhouse study," *Remote Sensing*, vol. 12, no. 22, pp. 3809–, Nov. 20, 2020. DOI: 10.3390/rs12223809

[5] C. Ioannidis, A.-M. Boutsi, G. Tsingenopoulos, S. Soile, R. Chliverou, and C. Potsiou, “Paving the way for last-mile delivery in greece: Data-driven performance analysis with a customized quadrotor,” *Drones*, vol. 8, no. 1, pp. 6–6, Dec. 29, 2023. DOI: 10.3390/drones8010006

[6] R. J. Wallace, J. M. Loffi, S. M. Vance, J. Jacob, J. C. Dunlap, and T. Mitchell, “Pilot visual detection of small unmanned aircraft systems (suas) equipped with strobe lighting,” *Journal of Aviation Technology and Engineering*, vol. 7, no. 2, pp. 5–, Apr. 13, 2018. DOI: 10.7771/2159-6670.1177

[7] M. Aboutalebi et al., “Incorporation of unmanned aerial vehicle (uav) point cloud products into remote sensing evapotranspiration models,” *Remote sensing*, vol. 12, no. 1, pp. 50–, Dec. 20, 2019. DOI: 10.3390/rs12010050

[8] M. D. Gregorio, M. Romano, M. Sebillo, G. Vitiello, and A. Vozella, “Improving human ground control performance in unmanned aerial systems,” *Future Internet*, vol. 13, no. 8, pp. 188–203, Jul. 22, 2021. DOI: 10.3390/fi13080188

[9] M. Ribeiro, J. Ellerbroek, and J. Hoekstra, “Velocity obstacle based conflict avoidance in urban environment with variable speed limit,” *Aerospace*, vol. 8, no. 4, pp. 93–, Apr. 1, 2021. DOI: 10.3390/aerospace8040093

[10] A. C. Canolla, M. B. Jamoom, and B. Pervan, “Unmanned aircraft systems detect and avoid sensor hybrid estimation error analysis,” in *17th AIAA Aviation Technology, Integration, and Operations Conference*, 2017, p. 4384.

[11] K. Shimasaki, N. Fujiwara, S. Hu, T. Senoo, and I. Ishii, “High-frame-rate video-based multicopter tracking system using pixel-level short-time fourier transform,” *Journal of Intelligent & Robotic Systems*, vol. 103, no. 2, pp. 36–, Sep. 30, 2021. DOI: 10.1007/s10846-021-01483-2

[12] G. Dutta and P. Goswami, “Application of drone in agriculture: A review,” *International Journal of Chemical Studies*, vol. 8, no. 5, pp. 181–187, Oct. 1, 2020. DOI: 10.22271/chemi.2020.v8.i5d.10529

[13] S. Showkat and S. Qureshi, “Securing the internet of things through blockchain approach:security architectures, consensus algorithms, enabling technologies, open issues, and research directions,” *International Journal of Computing and Digital Systems*, vol. 13, no. 1, pp. 97–129, Jan. 31, 2023. DOI: 10.12785/ijcds/130109

[14] L. Yang, S. Li, C. Li, A. Zhang, and X. Zhang, “A survey of unmanned aerial vehicle flight data anomaly detection: Technologies, applications, and future directions,” *Science China Technological Sciences*, vol. 66, no. 4, pp. 901–919, Mar. 15, 2023. DOI: 10.1007/s11431-022-2213-8

[15] W. H. Semke et al., “Analysis of radar and ads-b influences on aircraft detect and avoid (daa) systems,” *Aerospace*, vol. 4, no. 3, pp. 49–, Sep. 18, 2017. DOI: 10.3390/aerospace4030049

[16] R. Calderón, J. A. Navas-Cortes, and P. J. Zarco-Tejada, “Early detection and quantification of verticillium wilt in olive using hyperspectral and thermal imagery over large areas,” *Remote Sensing*, vol. 7, no. 5, pp. 5584–5610, May 4, 2015. DOI: 10.3390/rs70505584

[17] E. Salamí, C. Barrado, and E. Pastor, “Uav flight experiments applied to the remote sensing of vegetated areas,” *Remote Sensing*, vol. 6, no. 11, pp. 11 051–11 081, Nov. 11, 2014. DOI: 10.3390/rs61111051

[18] G. Gonçalves, U. Andriolo, L. M. S. Gonçalves, P. Sobral, and F. Bessa, “Quantifying marine macro litter abundance on a sandy beach using unmanned aerial systems and object-oriented machine learning methods,” *Remote Sensing*, vol. 12, no. 16, pp. 2599–, Aug. 12, 2020. DOI: 10.3390/rs12162599

[19] H. Li, Y. Chen, J. Liu, Z. Zhang, and H. Zhu, “Unmanned aircraft system applications in damage detection and service life prediction for bridges: A review,” *Remote Sensing*, vol. 14, no. 17, pp. 4210–4210, Aug. 26, 2022. DOI: 10.3390/rs14174210

[20] C. Eschmann, C.-M. Kuo, C.-H. Kuo, and C. Boller, “High-resolution multisensor infrastructure inspection with unmanned aircraft systems,” *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XL-1/W2, pp. 125–129, Aug. 16, 2013. DOI: 10.5194/isprsarchives-xl-1-w2-125-2013

[21] M. Vélez-Nicolás, S. García-López, L. Barbero, V. Ruiz-Ortiz, and Á. Sánchez-Bellón, “Applications of unmanned aerial systems (uass) in hydrology: A review,” *Remote Sensing*, vol. 13, no. 7, pp. 1359–, Apr. 1, 2021. DOI: 10.3390/rs13071359

[22] A. Hamidisepehr, M. P. Sama, J. S. Dvorak, O. Wendroth, and M. D. Montross, “Classifying reflectance targets under ambient light conditions using passive spectral measurements.,” *Sensors (Basel, Switzerland)*, vol. 20, no. 18, pp. 5375–, Sep. 19, 2020. DOI: 10.3390/s20185375

[23] M. Hong, D. J. Bremer, and D. van der Merwe, “Evaluating small unmanned aerial systems for detecting drought stress on turfgrass,” *Kansas Agricultural Experiment Station Research Reports*, vol. 4, no. 6, pp. 3–, Jan. 1, 2018. DOI: 10.4148/2378-5977.7593

[24] M. B. Jamoom, A. Canolla, B. Pervan, and M. Joerger, “Unmanned aircraft system sense and avoid integrity: Intruder linear accelerations and analysis,” *Journal of Aerospace Information Systems*, vol. 14, no. 1, pp. 53–67, 2017.

[25] D. D. Nguyen, J. Rohacs, and D. Rohacs, “Autonomous flight trajectory control system for drones in smart city traffic management,” *ISPRS International Journal of Geo-Information*, vol. 10, no. 5, pp. 338–, May 17, 2021. DOI: 10.3390/ijgi10050338

[26] F. Z. Saadaoui, N. Cheggaga, and N. E. H. Djabri, “Multi-sensory system for uavs detection using bayesian inference,” *Applied Intelligence*, vol. 53, no. 24, pp. 29 818–29 844, Nov. 4, 2023. DOI: 10.1007/s10489-023-05027-z

[27] A. Xavier, B. Hall, A. A. Hearst, K. A. Cherkauer, and K. M. Rainey, "Genetic architecture of phenomic-enabled canopy coverage in glycine max.," *Genetics*, vol. 206, no. 2, pp. 1081–1089, Jun. 1, 2017. DOI: 10.1534/genetics.116.198713

[28] J. Lenzi, A. F. Barnas, A. A. ElSaid, T. Desell, R. F. Rockwell, and S. N. Ellis-Felege, "Artificial intelligence for automated detection of large mammals creates path to upscale drone surveys.," *Scientific reports*, vol. 13, no. 1, pp. 947–, Jan. 18, 2023. DOI: 10.1038/s41598-023-28240-9

[29] E. G. S. Nascimento, A. N. Furtado, R. Badaró, and L. Knop, "The new technologies in the pandemic era," *JOURNAL OF BIOENGINEERING AND TECHNOLOGY APPLIED TO HEALTH*, vol. 3, no. 2, pp. 134–164, Nov. 29, 2020. DOI: 10.34178/jbth.v3i2.122

[30] M. A. Lopez, F. F. Moreira, A. Hearst, K. Cherkauer, and K. M. Rainey, "Physiological breeding for yield improvement in soybean: Solar radiation interception-conversion, and harvest index.," *TAG. Theoretical and applied genetics. Theoretische und angewandte Genetik*, vol. 135, no. 5, pp. 1477–1491, Mar. 11, 2022. DOI: 10.1007/s00122-022-04048-5

[31] A. Oztekin, C. Flass, and X. Lee, "Development of a framework to determine a mandatory safety baseline for unmanned aircraft systems," *Journal of Intelligent & Robotic Systems*, vol. 65, no. 1, pp. 3–26, Aug. 26, 2011. DOI: 10.1007/s10846-011-9578-0

[32] H. S. Sangha, A. Sharda, W. Schapaugh, and D. Walta, "Evaluation of multispectral sensors for assessing pigment index in soybean," *Acta Scientific Agriculture*, pp. 13–23, Apr. 1, 2022. DOI: 10.31080/asag.2022.06.1115

[33] A. F. Rees et al., "The potential of unmanned aerial systems for sea turtle research and conservation: A review and future directions," *Endangered Species Research*, vol. 35, pp. 81–100, Feb. 19, 2018. DOI: 10.3354/esr00877

[34] D. Gatziolis and R. J. McGaughey, "Reconstructing aircraft trajectories from multi-return airborne laser-scanning data," *Remote Sensing*, vol. 11, no. 19, pp. 2258–, Sep. 27, 2019. DOI: 10.3390/rs11192258

[35] G. Gonçalves, D. N. Gonçalves, Á. Gómez-Gutiérrez, U. Andriolo, and J. A. Pérez-Alvárez, "3d reconstruction of coastal cliffs from fixed-wing and multi-rotor uas: Impact of sfm-mvs processing parameters, image redundancy and acquisition geometry," *Remote Sensing*, vol. 13, no. 6, pp. 1222–, Mar. 23, 2021. DOI: 10.3390/rs13061222

[36] N. Elmeseiry, N. Alshaer, and T. Ismail, "A detailed survey and future directions of unmanned aerial vehicles (uavs) with potential applications," *Aerospace*, vol. 8, no. 12, pp. 363–, Nov. 25, 2021. DOI: 10.3390/aerospace8120363

[37] J. Zhao et al., "Path planning research of a uav base station searching for disaster victims' location information based on deep reinforcement learning.," *Entropy (Basel, Switzerland)*, vol. 24, no. 12, pp. 1767–1767, Dec. 2, 2022. DOI: 10.3390/e24121767

[38] J. Elston, E. W. Frew, D. Lawrence, P. Gray, and B. Argrow, "Net-centric communication and control for a heterogeneous unmanned aircraft system," *Journal of Intelligent and Robotic Systems*, vol. 56, no. 1, pp. 199–232, May 22, 2009. DOI: 10.1007/s10846-009-9334-x

[39] J. Geipel, J. Link, J. A. Wirwahn, and W. Claupein, "A programmable aerial multispectral camera system for in-season crop biomass and nitrogen content estimation," *Agriculture*, vol. 6, no. 1, pp. 4–, Jan. 18, 2016. DOI: 10.3390/agriculture6010004

[40] C. Torens, F. Nikodem, J. C. Dauer, S. Schirmer, and J. S. Dittrich, "Geofencing requirements for onboard safe operation monitoring," *CEAS Aeronautical Journal*, vol. 11, no. 3, pp. 767–779, May 16, 2020. DOI: 10.1007/s13272-020-00451-0

[41] J. Hu, T. Wang, H. Zhang, Q. Pan, J. Zhang, and Z. Xu, "A review of rule-based collision avoidance technology for autonomous uav," *Science China Technological Sciences*, vol. 66, no. 9, pp. 2481–2499, Aug. 21, 2023. DOI: 10.1007/s11431-022-2264-5

[42] J. Farlik, M. Kratky, J. Casar, and V. Stary, "Multispectral detection of commercial unmanned aerial vehicles.," *Sensors (Basel, Switzerland)*, vol. 19, no. 7, pp. 1517–, Mar. 28, 2019. DOI: 10.3390/s19071517

[43] M. Solla et al., "A building information modeling approach to integrate geomatic data for the documentation and preservation of cultural heritage," *Remote Sensing*, vol. 12, no. 24, pp. 4028–, Dec. 9, 2020. DOI: 10.3390/rs12244028

[44] E. R. Hunt and A. J. Stern, "Evaluation of incident light sensors on unmanned aircraft for calculation of spectral reflectance.," *Remote Sensing*, vol. 11, no. 22, pp. 2622–, Nov. 9, 2019. DOI: 10.3390/rs11222622

[45] M. NiklaSS et al., "A collaborative approach for an integrated modeling of urban air transportation systems," *Aerospace*, vol. 7, no. 5, pp. 50–, Apr. 28, 2020. DOI: 10.3390/aerospace7050050