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*Systematic Review*

# Optimization and Tactical Deconfliction for Drone Search-and-Rescue in Low-Altitude Airspace: A Systematic Literature Review

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## Highlights

**What are the main findings?**

- This systematic review synthesizes 44 recent studies on drone-enabled search and rescue, with emphasis on swarm optimization, tactical deconfliction, and validation maturity.
- Deep reinforcement learning and bio-inspired metaheuristics dominate current SAR swarm optimization, but most studies remain limited to idealized software simulation.

**What are the implications of the main findings?**

- Future SAR swarm models should embed crewed–uncrewed deconfliction, right-of-way logic, communication degradation, and sensing uncertainty directly into optimization loops.
- Operational readiness requires stronger validation through hardware-in-the-loop testing, field trials, and realistic mixed-airspace disaster scenarios.

## Abstract

Unmanned Aerial Vehicle (UAV) swarms are increasingly deployed in search and rescue (SAR) missions to rapidly locate survivors. However, deploying autonomous swarms in low-altitude airspace shared with crewed rescue aircraft poses significant algorithmic and safety challenges. Following PRISMA 2020 guidelines, this systematic review synthesizes 44 peer-reviewed studies (2022–2026) to evaluate the literature across algorithmic optimization, reality-gap limitations, tactical deconfliction, and validation maturity. The synthesis reveals a consistent trend toward decentralized swarms, driven by Deep Reinforcement Learning in dynamic environments and by bio-inspired metaheuristics for static coverage. Despite these algorithmic advancements, the literature exhibits a severe reality gap: approximately 86% of evaluated models rely exclusively on idealized software simulations, abstracting away critical constraints like communication denial and sensor noise. Furthermore, most models assume uncontested airspace and lack the Manned–Unmanned Teaming (MUM-T) and tactical deconfliction protocols necessary for safe coexistence with rescue helicopters. To achieve true operational readiness within the critical "Golden 72 Hours" of disaster response, the discipline must transition toward hardware-in-the-loop and physical field trials, natively integrating airspace deconfliction into core swarm optimization loops.

**Keywords:** unmanned aerial vehicles (UAVs); drone swarms; search and rescue (SAR); deep reinforcement learning; manned–unmanned teaming (MUM-T); coverage path planning (CPP); tactical deconfliction



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## 1. Introduction

Search-and-rescue (SAR) operations take place under severe time pressure and difficult environmental conditions. After earthquakes, floods, landslides, wildfires, maritime emergencies, and remote-terrain incidents, responders must locate survivors while dealing with damaged infrastructure, unstable terrain, poor visibility, disrupted communications, and incomplete situational information. Large-scale disasters also produce substantial human and economic losses, although available disaster data remain imperfect for planning and evaluation [1]. In SAR, time is not simply a logistical concern; it directly shapes survival outcomes. Chiu et al. [2] reported that the survival ratio for earthquake victims rescued within 24 h averaged 74%, compared with 22% on the third day and 6% on the fifth day. Their findings support the "golden 72 h" principle while also showing how weather, terrain, environmental conditions, and traffic flow can limit rescue efficiency.

### 1.1. Role of Drones in SAR

Drone systems have become a major focus in SAR research because they can quickly collect aerial data, reach hazardous areas, and support search activities where ground teams or crewed aircraft face elevated risk. UAVs are especially useful because they offer mobility, accessibility, rapid deployment, hovering capability, and the capacity to carry visual, infrared, thermal, acoustic, and other sensing payloads [3]. Interest in aerial SAR support predates the current swarm era: camera-equipped mini-UAVs were flown in wilderness SAR nearly two decades ago [4], and cooperative multi-robot SAR has since become a sustained line of research [5]. Such sensing and mobility capabilities are valuable in disaster zones where blocked roads, debris fields, smoke, floodwater, mountainous terrain, or unstable structures restrict ground access. Drones can also support real-time mapping, target detection, communication relay, and situational awareness for incident commanders and rescue crews. Even so, drone SAR is not only a sensing problem. A deployable SAR system must decide where drones should search, how coverage should be divided, how plans should adjust to new information, how battery limits should be managed, and how operations should remain safe when other aircraft are present. Throughout the present review, the terms drone, unmanned aerial vehicle (UAV), and unmanned aircraft are used interchangeably to denote uncrewed aircraft operating under remote pilotage or autonomy; the regulatory term small unmanned aircraft system (sUAS) is used only when quoting U.S. rule language.

### 1.2. Algorithmic Optimization and Swarm Coordination

The algorithmic core of drone SAR typically includes coverage path planning, search-space partitioning, target localization, task allocation, trajectory generation, and cooperative control. Single-drone models can support small-area searches, but disaster environments are often too large, uncertain, or time-sensitive for one platform. Multi-UAV systems can distribute search tasks across several aircraft, improving coverage speed and reducing dependence on a single vehicle. That advantage, however, introduces coordination complexity. Ghauri et al. [6] described multi-UAV task allocation as a cooperative decision-making problem shaped by time, energy, and mission-completion constraints. Similarly, Xiao et al. [7] noted that heterogeneous UAV coverage path planning is commonly treated as a non-deterministic polynomial hard problem, requiring decomposition or approximation strategies as the number of UAVs and search regions increases.

Recent drone SAR and swarm-planning studies increasingly use optimization and artificial intelligence methods, including deep reinforcement learning, multi-agent reinforcement learning, genetic algorithms, particle swarm optimization, ant colony optimization, clustering-based partitioning, auction mechanisms, consensus-based bundle algorithms, graph search, rapidly exploring random trees, and hybrid approaches. Li et al. [8] organized multi-UAV path-planning methods around mission type and environmental dynamics, emphasizing tradeoffs among responsiveness, safety, scalability, energy use, sensing uncertainty, communication reliability, and sim-to-real transfer. In SAR, these tradeoffs matter operationally because the mathematically optimal search plan may not be the safest or most feasible plan under battery constraints, wind, terrain masking, communication loss, degraded sensors, or changing survivor locations.

### 1.3. Airspace Safety and Tactical Deconfliction

A second challenge involves the low-altitude airspace where drone SAR occurs. Disaster airspace is rarely empty. Rescue helicopters, law-enforcement aircraft, medical evacuation aircraft, firefighting aircraft, news aircraft, and additional drones may operate near the same incident area. Under U.S. small UAS operating rules, a small, unmanned aircraft must yield right of way to all aircraft, airborne vehicles, and launch or reentry vehicles, and it may not operate so close to another aircraft as to create a collision hazard [9]. For that reason, an optimized search pattern remains incomplete unless it also addresses airspace safety, right-of-way requirements, detect-and-avoid logic, separation assurance, and the possibility of tactical conflict with crewed aircraft. Manned–unmanned teaming has begun to receive attention in rotorcraft and emergency-service contexts. Roncolini et al. [10] examined a helicopter–drone teaming concept for Helicopter Emergency Medical Services in which a drone scouts the operating area, detects meteorological and environmental conditions, identifies obstacles, and supports path replanning. That teaming concept is relevant to SAR because helicopter rescue missions occur at low altitude and can be affected by unintended instrument meteorological conditions, terrain, obstacles, and incomplete local weather information. Collision-risk studies further show that mixed manned–unmanned airspace requires explicit modeling of communication, navigation, surveillance, human factors, collision-avoidance equipment, meteorological conditions, positioning errors, and target safety levels [11,12]. These requirements are related to, but distinct from, intra-swarm collision avoidance: a drone swarm may avoid collisions among its own members while still failing to maintain safe separation from a crewed helicopter entering the same search area.

### 1.4. Gap in the Existing Literature

Existing reviews provide useful foundations but do not fully resolve the combined problem of SAR optimization and airspace safety. Lyu et al. [3] reviewed UAV applications in SAR, including sensing, target localization, path planning, task assignment, and collision avoidance. Ghauri et al. [6] reviewed multi-UAV task allocation algorithms for SAR scenarios. They identified open issues involving dynamic events, no-communication environments, limited inter-UAV communication, scalability, and human-UAV task allocation. Li et al. [8] synthesized multi-UAV swarm path-planning algorithms and emphasized scenario-conditioned tradeoffs, digital-twin validation, and safety-aware collision avoidance. These reviews are valuable, but their primary focus does not fall on the intersection of SAR optimization, tactical deconfliction, and operational validation in mixed low-altitude airspace. As a result, the literature still lacks a focused synthesis that shows whether drone SAR algorithms are being developed for operational aviation systems or primarily as computational search models. Table 1 positions the present review against these prior syntheses. To the authors' knowledge, no previous PRISMA-guided review has jointly synthesized SAR swarm optimization, crewed-aircraft tactical deconfliction, and validation maturity for low-altitude disaster airspace.

**Table 1.** Comparison of the present review with related prior reviews.

| Review | Primary Scope | SAR-Specific | Crewed-Aircraft Deconfliction/ MUM-T | Validation-Maturity Synthesis | Item-Level Quality Appraisal |
|---|---|---|---|---|---|
| Queralta et al. [5] | Multi-robot SAR: planning, coordination, perception, active vision | Yes | Not central | Not central | No |
| Lyu et al. [3] | UAV SAR applications: sensing, target localization, path planning, task assignment | Yes | Not central | Not central | No |
| Ghauri et al. [6] | Multi-UAV task-allocation algorithms for SAR scenarios | Yes | Not central | Limited | No |
| Li et al. [8] | Multi-UAV swarm path-planning algorithms across mission types | No | Not central | Limited | No |
| Present review | SAR swarm optimization coupled with tactical deconfliction, MUM-T, and validation maturity in mixed low-altitude airspace | Yes | Yes (RQ2) | Yes (RQ3) | Yes (8 items, 3 reviewers) |

The distinction matters because disaster response is a dynamic aerospace environment. Survivors may move, weather may change, batteries may deplete faster than expected, communication links may degrade, maps may be outdated, and crewed rescue aircraft may enter the search volume. Algorithms that perform well in static grid simulations may not transfer to these conditions without additional assumptions, sensing, communication, and separation logic. A systematic review is therefore needed to evaluate not only which algorithms are used, but also the operational assumptions that support them, the extent to which tactical airspace risk is addressed, and the degree to which validation has moved beyond idealized simulation. These strategic and tactical layers, spanning the pre-flight and in-flight phases of drone-based SAR, are summarized in Figure 1 and frame the questions this review addresses.

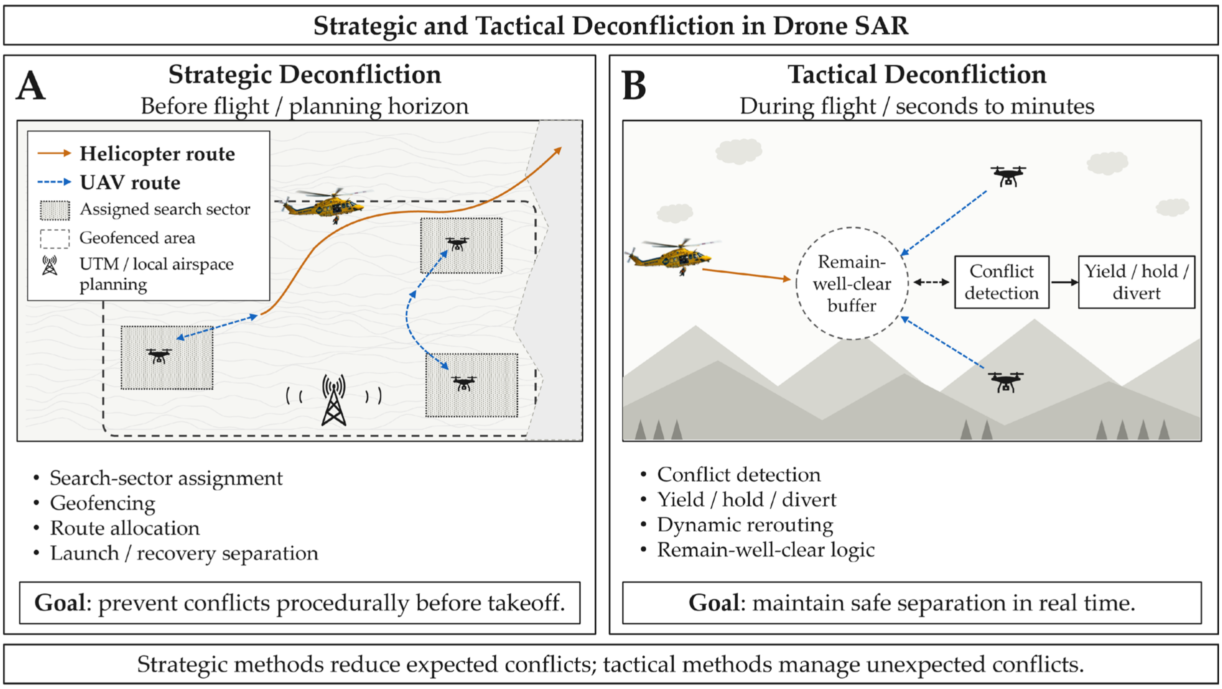


**Figure 1.** Strategic (pre-flight) versus tactical (in-flight) deconfliction in drone-based SAR. (**A**) Pre-flight separation via search-sector assignment, geofencing, route allocation, and launch/recovery separation within UTM/local-airspace constraints. (**B**) In-flight conflict detection and yield/hold/divert with dynamic rerouting inside a remain-well-clear buffer.

*1.5. Review Objective and Research Questions*

The present review synthesizes peer-reviewed research on drone SAR in low-altitude airspace, with particular attention to algorithmic optimization, swarm coordination, tactical deconfliction, manned–unmanned teaming, and operational validation. Specifically, the review aims to:

- Identify dominant algorithmic families used in drone SAR;
- Assess how studies address safe coexistence with crewed rescue aircraft;
- Evaluate whether validation methods reflect realistic SAR conditions, including dynamic targets, communication degradation, environmental constraints, and field testing.

The review addresses the following research questions:

**RQ1:** What are the prevailing algorithmic frameworks, such as deep reinforcement learning and bio-inspired swarm intelligence, used to optimize multi-drone coverage path planning and dynamic task allocation in unstructured, low-altitude disaster environments?
**RQ2:** How do current models ensure tactical deconfliction and safe manned–unmanned teaming when autonomous drone swarms share chaotic, low-altitude airspace with crewed rescue helicopters?
**RQ3:** To what extent are these optimizations and tactical deconfliction algorithms validated in operationally realistic environments, such as through dynamic survivor mobility, communication denial, hardware-in-the-loop testing, and field trials rather than static computer simulations?

Organizing the literature around these questions helps build a focused evidence base for drone SAR as both an optimization problem and an aviation safety problem. The intended contribution is a structured synthesis that connects algorithmic search performance with the operational requirements of low-altitude rescue airspace, thereby clarifying where the current literature is mature, where assumptions remain unrealistic, and where future research must better integrate optimization, deconfliction, and validation. Figure 2 summarizes the operational logic that motivates the review, linking SAR mission objectives with algorithmic optimization, traffic-state awareness, tactical deconfliction, and validation maturity.

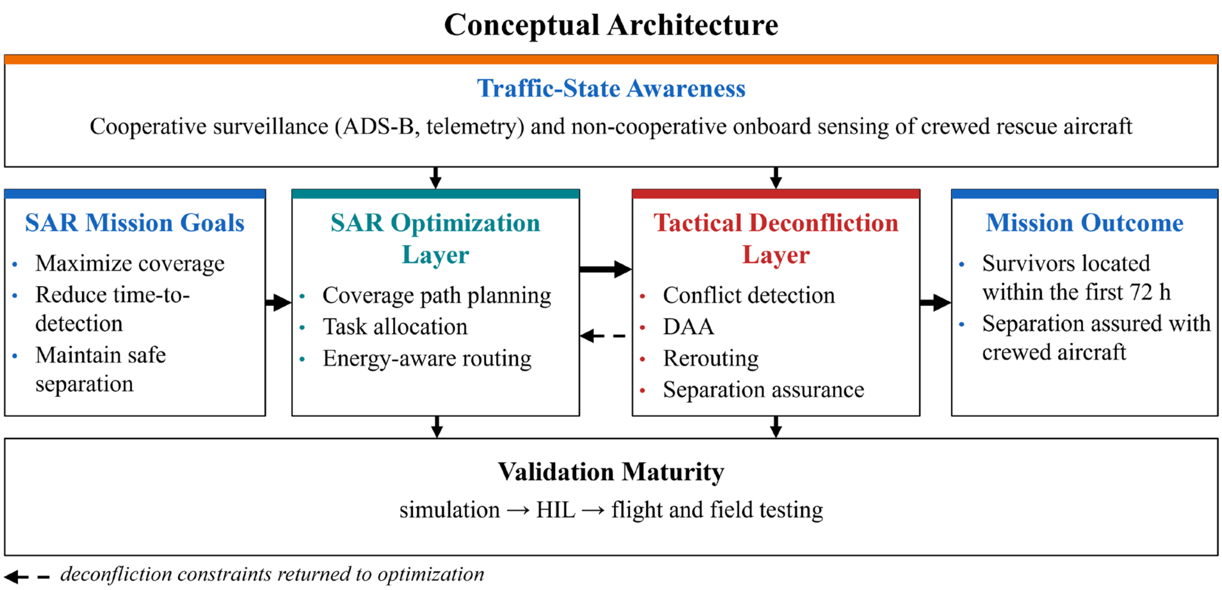


**Figure 2.** Conceptual architecture linking SAR mission optimization with traffic-aware tactical deconfliction in low-altitude airspace.

## 2. Methodology

The review was conducted and reported in accordance with the PRISMA 2020 statement for systematic reviews [13].The completed PRISMA 2020 checklist is available as Supplementary Material. The review protocol was not registered with PROSPERO or another systematic review registry because the study focused on the engineering, UAV autonomy, and aerospace operations literature rather than on clinical or health intervention evidence. The search strategy, eligibility criteria, screening process, data extraction procedure, and synthesis approach are reported in the following subsections.

The methodology was designed to identify, screen, appraise, and synthesize recent peer-reviewed research on drone-enabled search-and-rescue (SAR) in low-altitude operational environments. The review focused on studies addressing algorithmic optimization for SAR mission execution, tactical deconfliction in mixed airspace, or their intersection. Because the objective was to evaluate drone SAR as an operational aerospace system rather than as a generic airspace-management problem, the search and screening procedures applied a strict disaster-assistance scope.

During manuscript preparation, the authors used Qwen 3.6-35B-A3B, a locally hosted large language model, for high-level structural planning and organizational support prior to drafting. The tool was not used to conduct database searches, determine study eligibility, make screening decisions, extract data, score methodological quality, generate results, manipulate data, or create images. Grammarly 1.2.259.1886 was used for automated spelling, grammar, and readability checks. All AI-assisted and automated suggestions were reviewed, edited, and verified by the authors. The authors take full responsibility for the accuracy, integrity, originality, and final content of the manuscript.

### *2.1. Eligibility Criteria*

Eligibility criteria were structured using a Population–Concept–Context framework. The population of interest comprised unmanned aerial vehicles (UAVs), autonomous drones, drone swarms, heterogeneous UAV teams, and multi-agent aerial robotic systems. The concept domain included algorithmic optimization (e.g., coverage path planning, reinforcement learning, metaheuristic optimization) and tactical deconfliction (e.g., obstacle avoidance, manned–unmanned teaming, separation logic). The primary context domain comprised time-critical SAR missions in unstructured, low-altitude environments (e.g., post-disaster search, wilderness rescue, maritime SAR). Recognizing that the deconfliction and airspace-safety mechanisms central to RQ2 are frequently developed in adjacent low-altitude domains, a secondary category of transfer evidence was also admitted. Transfer evidence comprised studies addressing generic detect-and-avoid (DAA), non-cooperative threat resolution, wildfire suppression, or manned–unmanned teaming (MUM-T) in shared low-altitude airspace that, although not framed within an explicit SAR scenario, develop separation-assurance or deconfliction methods directly transferable to crewed–uncrewed coexistence in SAR operations. Such studies were eligible solely for their contribution to RQ2 and were flagged as transfer evidence during data extraction to distinguish them from studies set in an explicit SAR context.

To ensure high methodological quality, built-in database filters were applied to restrict eligibility strictly to peer-reviewed journal articles and conference proceedings published in English. Preprints, technical white papers, and non-peer-reviewed commentaries were systematically excluded.

### *2.2. Information Sources and Search Strategy*

The literature search was conducted across three technical databases selected for their relevance to aerospace engineering and autonomous systems: *IEEE Xplore*, *AIAA Aerospace*

*Research Central*, and *Web of Science Core Collection*. The final search across all three databases was executed on 5 May 2026. The search was limited to the recent literature published between 2022 and 2026.

The search strategy used Boolean strings designed to capture the intersection of SAR optimization, drone swarms, manned–unmanned interaction, and tactical deconfliction. Three primary Boolean search strings were applied across the selected databases, with database-specific syntax adjustments where necessary:

1. ("Search and Rescue" OR "SAR") AND ("drone swarm" OR "UAV swarm")
2. ("drone" OR "UAV") AND ("helicopter" OR "manned aircraft") AND ("deconfliction" OR "collision avoidance") AND ("SAR" OR "Search and Rescue")
3. ("drone" OR "UAV") AND ("helicopter" OR "manned aircraft") AND ("deconfliction")

The first search string targeted SAR-specific drone swarm and multi-UAV studies. The second search string targeted studies that explicitly connected UAVs, crewed aircraft, deconfliction, and SAR. The third search string broadened retrieval for manned–unmanned deconfliction studies that may have contained operationally relevant low-altitude safety models but did not necessarily use SAR in the title, abstract, or keywords. Retrieved records were assessed against the eligibility criteria to determine whether their deconfliction content applied to SAR or disaster-response airspace. Duplicate records were removed before title and abstract screening. No study was included or excluded solely by automation. Automated tools, when used, were limited to record management, search export organization, and matrix preparation rather than eligibility decision-making.

A targeted supplementary search was performed in Scopus to broaden source and keyword coverage beyond the original three databases. The expanded Boolean string combined the population terms ("drone swarm(s)", "UAV swarm", "multi-UAV", "multi-drone", "cooperative UAV") with additional keywords ("path planning", "mission planning", "task allocation", "collision avoidance", "cooperative search", "routing") and disaster-context terms ("search and rescue", "disaster rescue", "emergency rescue", "post-disaster", "disaster management", "emergency response", "disaster area(s)"), limited to English-language journal articles and conference papers published between 2022 and 2026. The search returned 256 records. After removal of 11 records already included in the review, 245 unique records were screened at title and abstract level against the eligibility criteria of Section 2.1; because the broadened keywords traded precision for recall, most records fell outside the disaster-assistance scope, and 12 reports proceeded to full-text assessment. The supplementary search was restricted to Scopus, as acknowledged in Section 4.4 [14]. Of the 12 full-text reports, two fell outside the disaster-assistance scope and the remaining ten met the established inclusion criteria of Section 2.1; all ten were integrated [15–24]. The ten studies contribute measured energy consumption, quantified communication overhead, hybrid metaheuristics, three-dimensional disaster terrain, maritime coverage planning, connectivity-aware search, and validation beyond software simulation. In the PRISMA 2020 flow diagram (Figure 3), the supplementary records form the separate "identification of studies via other methods" stream, and the ten studies add to the final total (34 + 10 = 44).

### *2.3. Selection Process and Data Collection*

Search results (total $n$ = 498) from the original database search were exported into structured screening records. Deduplication was performed procedurally: first, reference management software was utilized to algorithmically identify and remove exact matches, followed by a manual verification step by the authors to remove close-match duplicates (e.g., early conference papers later published as expanded journal articles).

Selection proceeded in two stages. Two authors independently conducted title-and-abstract screening and full-text eligibility assessment using the predefined criteria, assigning a provisional decision to each potentially eligible record. Disagreements and borderline cases were resolved through discussion and consensus. A stricter relevance rule was applied during full-text screening to prioritize studies with extractable methods and metrics, and explicit SAR/mixed-airspace relevance. Aggregate reasons for the 81 database-search full-text exclusions are provided in Table A1.

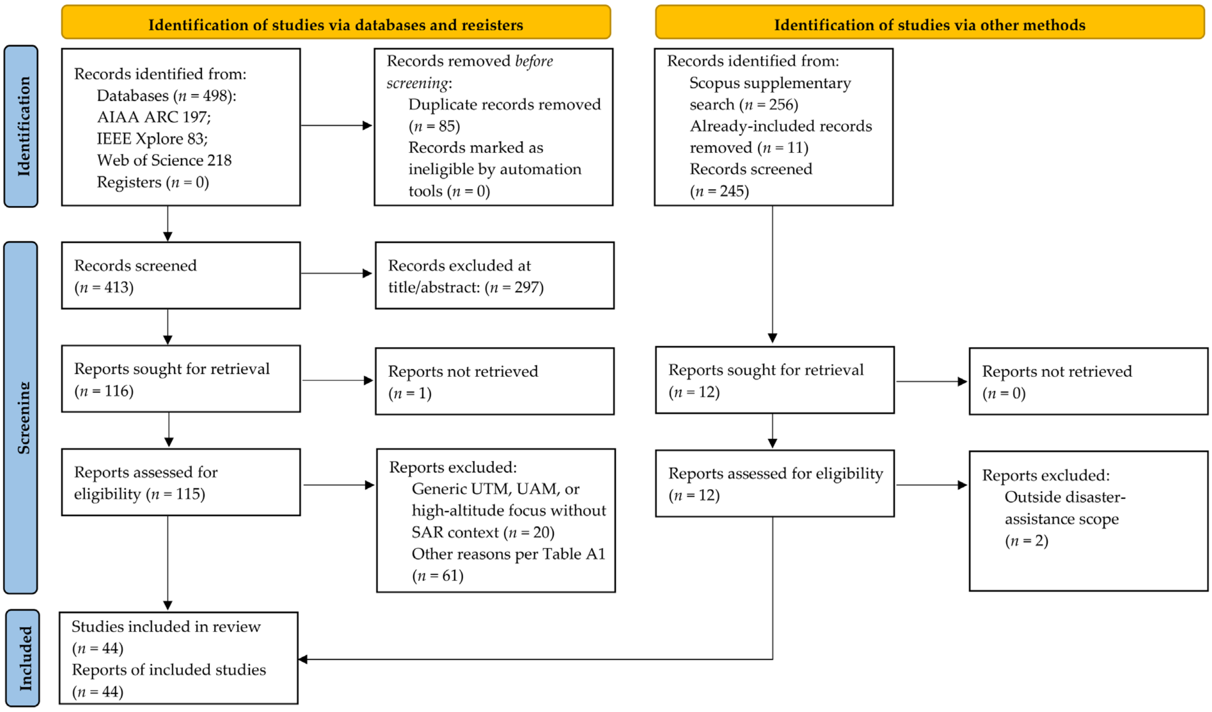


**Figure 3.** PRISMA 2020 Diagram. The right-hand column reports the supplementary search stream (Section 2.2); diagram template from [13].

Data extraction was independently performed by two reviewers using a standardized Microsoft Excel matrix. To guarantee fidelity, a third reviewer cross-verified 100% of the extracted data against the original full-text reports to resolve any discrepancies. Extracted variables included bibliographic information, vehicle configuration, algorithm family, tactical deconfliction models, validation type, and performance metrics.

### 2.4. Narrative Synthesis and Coding Procedure

Due to the significant heterogeneity in algorithmic architectures, simulation environments, and performance metrics across the 44 included studies, a quantitative meta-analysis was not methodologically feasible. Instead, a rigorous narrative synthesis was conducted.

During the coding procedure, the extracted data were systematically categorized into three thematic dimensions: (1) SAR optimization algorithms (e.g., bio-inspired meta-heuristics vs. Deep Reinforcement Learning frameworks), (2) reality-gap limitations (e.g., sensor fusion approaches, communication fragility), and (3) tactical deconfliction maturity in mixed airspace. This structured coding procedure enabled a standardized qualitative comparison of computational search performance with operational aviation safety across all of the included literature.

### 2.5. Study Risk of Bias and Quality Assessment

Study quality, reporting transparency, and methodological credibility were assessed using a custom eight-item engineering reporting and methodological appraisal checklist informed by the Mixed Methods Appraisal Tool framework [25]. The MMAT was not applied as a direct clinical or social-science quality instrument. Instead, its structured appraisal logic informed an engineering-oriented checklist adapted for research in simulation, robotics, autonomy, and aerospace systems.

The eight appraisal questions assessed the following domains:

1. Is the study objective or research question clearly stated?
2. Is the UAV, SAR, deconfliction, ADS-B, or mixed-airspace method described with enough detail to support interpretation?
3. Is the selected method appropriate for the stated SAR optimization or deconfliction problem?
4. Are comparators, baselines, benchmarks, or reference cases clearly described and appropriate?
5. Are performance metrics clearly defined and aligned with SAR mission effectiveness, deconfliction safety, or operational feasibility?
6. Are the scenarios operationally realistic enough for SAR, helicopter interaction, low-altitude airspace, UTM, U-space, or mixed manned–unmanned operations?
7. Does the study address uncertainty, latency, packet loss, degraded communications, platform failure, sensing limitations, or other operational constraints?
8. Is validation maturity adequate, and is enough information provided to judge reproducibility?

Three reviewers independently applied the appraisal checklist to each included study using Microsoft Excel. Each item was scored as yes = 1, partly = 0.5, or no = 0. Ratings were compared item by item, and disagreements were resolved through consensus discussion. The final consensus score for each study was not calculated by arithmetically averaging the reviewers' overall percentages. Instead, consensus was determined item by item, using the majority rating when at least two reviewers agreed, and a provisional median item-level rating, flagged for further review, when all three differed. Final judgments categorized studies as low concern, some concern, or high concern based on the pattern of item-level ratings, with particular focus on identifying the "reality gap" in studies that relied solely on idealized computer simulations without physical hardware validation. The Low/Some/High Concern thresholds were defined before scoring commenced: Low Concern required a consensus score $\geq$ 75% with at most one "no" rating; Some Concern corresponded to 50–74% or two "no" ratings; and High Concern to <50% or three or more "no" ratings. Across all 44 included studies (three raters $\times$ eight items), raw pairwise exact agreement was 62.3% (79.8% with linear ordinal weighting), corresponding to chance-corrected coefficients of Gwet's AC1 = 0.52 and linearly weighted AC2 = 0.68. Gwet's coefficients are reported instead of Fleiss' $\kappa$ because the strong prevalence of "yes" ratings inflates $\kappa$'s chance-agreement term and yields paradoxically low values despite high observed agreement [26]. All residual disagreements were resolved to full consensus. The ten studies added through the supplementary search were appraised through the identical procedure: the same three reviewers scored each study independently, and consensus was determined item by item under the same rules.

## 3. Results

### *3.1. Study Selection*

The systematic identification and screening of the literature adhered strictly to the PRISMA 2020 guidelines (Figure 3) to ensure a robust and reproducible curation process [13]. Initially, 498 records were identified from academic databases, comprising 197 from AIAA Aerospace Research Central, 83 from IEEE Xplore, and 218 from the Web of Science. After removing 85 duplicate records, 413 unique studies advanced to the title and abstract screening phase. This initial screening eliminated 297 records, leaving 116 reports sought for full-text retrieval. Following the successful retrieval of 115 full-text reports, a rigorous eligibility assessment was conducted. During this phase, 81 reports were excluded with specific reasons, primarily because they focused entirely on generic Unmanned Traffic Management (UTM), Urban Air Mobility (UAM), or high-altitude civil aviation without a clear application to Search and Rescue (SAR) contexts. Ultimately, this strict filtration process yielded 34 core studies from the database stream. A subsequent supplementary search (Section 2.2), reported as a separate identification stream under PRISMA 2020, returned 256 records, of which 12 reports were assessed in full text and ten studies were integrated. The final curated synthesis therefore comprises 44 core studies (34 identified via databases and ten via the supplementary Scopus search). Detailed full-text exclusion reasons are provided in Table A1.

### 3.2. Study Characteristics

The 44 included studies (published between 2022 and 2026) present a highly specialized yet deeply siloed research landscape in low-altitude aerospace engineering. As summarized in Table 2, the literature spans a range of vehicle configurations, from single UAVs to massive heterogeneous swarms, and operates across diverse operational contexts, including post-disaster zones, mountain ranges, wildfires, and maritime environments.

**Table 2.** Primary optimization methods and validation maturity ($n = 44$).

| Algorithm Family | Count | Primary Function in SAR/Deconfliction |
|---|---|---|
| Deep reinforcement learning (DRL)/MARL | 12 | Adaptive search, dynamic policy learning, and multi-agent coordination in unstructured 3D environments |
| Metaheuristics and bio-inspired methods | 8 | Swarm intelligence, including PSO, ACO, and GWO, applied to distributed coverage and redundancy minimization |
| Optimization and control | 10 | Route planning, mixed-integer linear programming, and constrained deployment |
| Domain-specific and graph-search methods | 9 | Scenario-specific heuristics, A* algorithms, and geometric airspace division |
| Distributed control | 4 | Decentralized coordination, flocking behavior, and swarm relative localization |
| Probabilistic and Bayesian filtering | 1 | Hierarchical target tracking and swarm sensitivity estimation over time |

Note. SAR = search and rescue; DRL = deep reinforcement learning; MARL = multi-agent reinforcement learning; PSO = particle swarm optimization; ACO = ant colony optimization; GWO = grey wolf optimizer.

Validation maturity across these studies remains heavily skewed toward computer simulation. Approximately 86% (38 out of 44) of the included studies relied entirely on simulated software validations, revealing a notable gap between simulation-based findings and operational readiness. Only a select subset advanced to Hardware-in-the-Loop (HIL) experimental validations or physical field flight tests. The studies evaluate performance using diverse headline metrics. A tally of the Key Metrics column of Table 3 shows that search or mission time is the most prevalent objective, appearing as a headline metric in 14 of 44 studies and in approximately 20 when computational runtime and latency metrics (a distinct construct) are also counted; explicit energy or endurance metrics, by contrast, appear in only two studies (payload endurance, [27]; battery consumption, [16]). A full headline-metric frequency census is provided in Table A2, and the implications of the near-absence of measured energy metrics are discussed in Section 4.2.1. Table 3 summarizes the included studies.

**Table 3.** Summary of included studies ($n = 44$).

| Study | SAR Context | UAV Type | Algorithm Family | Deconfliction Modeled? | Validation Type | Key Metrics |
|---|---|---|---|---|---|---|
| Abdellatif et al. [28] | Post-Disaster | UAV Swarm (Edge-enabled) | Optimization/Control | No | Sim | Sensing performance, communication bandwidth |
| Aggarwal et al. [29] | Transfer: Wildfire | Multi-UAS | Optimization/Control | No | Sim | Path length, risk penalty |
| Al-Husseini et al. [30] | Transfer: Wildfire | UAV Swarm | DRL/MARL | No | Sim | Destruction minimization, suppression time |
| Aminzadeh & Khoshnood [15] | Post-Earthquake | Heterogeneous (fixed-wing + multirotor) | Distributed Control | No | Flight Test | Coverage rate, uncertainty convergence |
| Anastasiou et al. [31] | Maritime | UAV Swarm | Optimization/Control | No | Sim | Tracking error, area coverage |
| Andreeva-Mori et al. [32] | Transfer: Wildfire (MUM-T) | Heterogeneous (MUM-T) | Domain-Specific | Yes | Flight Test | Flight technical error, operational feasibility |
| Bassolillo et al. [33] | Post-Avalanche | UAV Swarm | Distributed Control | No | Sim | Standard deviation; mean absolute error |
| Bernardo et al. [34] | Target Search | UAV Swarm | Domain-Specific | No | Sim | Time to find target, completion time |
| Bialas et al. [35] | General SAR | Autonomous Swarm | DRL/MARL | No | Sim | Target localization time, coverage rate |
| Chen et al. [36] | Wildfire | Drone Swarm | Domain-Specific | No | Sim | Task assignment success, behavior accuracy |
| Chin et al. [37] | Disaster Response | Aerial Assets | Optimization/Control | No | Sim | Coverage time, Gini coefficient, distance |
| Cho et al. [21] | Maritime | Heterogeneous multi-UAV | Optimization/Control | No | Sim | Search completion time, computation time |
| Choi et al. [38] | Maritime | Multi-UAV | DRL/MARL | No | Sim | Search time, minimal path length |
| Du [23] | General SAR (3D terrain) | UAV Swarm | Domain-Specific | No | Sim | Computation time, memory usage |
| Gracia Otalvaro & Watson [39] | 3D Terrain | Multi-Drone | DRL/MARL | No | Sim | Targets found, episode steps to finish |
| Haddad et al. [16] | Post-Disaster | Drone Swarm (V-formation) | Domain-Specific | No | Sim | Victims found, battery consumption |
| Han et al. [17] | Post-Earthquake | Multi-UAV | Metaheuristics | No | Sim | Rescue cost, operation duration, UAVs deployed |
| He et al. [40] | General SAR | UAV | Domain-Specific | No | Sim | Object detection accuracy, trajectory efficiency |
| Hickling et al. [18] | General SAR (GNSS-denied) | Multi-UAV (quadrotors) | DRL/MARL | No | Flight Test | Task-allocation quality, navigation success |
| Horyna et al. [41] | General SAR | UAV Swarms | Distributed Control | No | Sim | Order metric, accuracy metric |
| Kareem et al. [42] | General SAR | UAV Swarm | Metaheuristics | No | Sim | Exploration score, redundancy ratio |
| Kareem et al. [43] | General SAR | Dual-Altitude Swarm | Metaheuristics | No | HIL * | Detection probability, mission time |
| Khetal et al. [44] | General SAR | UAV Swarms | DRL/MARL | No | Sim | Coverage rate, discovery time, bandwidth |
| Kopyt & Czaplińska [45] | General SAR | Multimodal Swarm | Domain-Specific | No | Flight Test | Target localization, swarm coordination |
| Leong [46] | Remote Terrain | Drone Swarms | DRL/MARL | No | Sim | Detection accuracy, latency, false positives |
| Lima et al. [47] | Maritime | Drone Swarm | Bayesian | No | Sim | Posterior distribution variance, sensitivity |
| Liu et al. [48] | Post-Disaster | Multi-UAV | Metaheuristics | No | Sim | Automation efficiency, rescue time |
| Liu et al. [49] | Mountain | Multi-UAV | DRL/MARL | No | Sim | Task completion rate, collisions, delay |

**Table 3.** *Cont.*

| Study | SAR Context | UAV Type | Algorithm Family | Deconfliction Modeled? | Validation Type | Key Metrics |
|---|---|---|---|---|---|---|
| Ma et al. [22] | Maritime | Multi-UAV | Metaheuristics | No | Sim | Total path length, urgent-target response time |
| Mather et al. [50] | General SAR | UAV Swarm | Domain-Specific | No | Sim | Target tracking, swarm effectiveness |
| Mukherjee et al. [51] | Transfer: Generic DAA | Multi-UAV | Optimization/Control | Yes | Sim | Right-of-way compliance, conflict resolution |
| Pradhan Shrestha et al. [52] | Transfer: Threat Avoidance | Multi-UAV | Domain-Specific | Yes | Sim | Threat avoidance, dynamic path planning |
| Pu et al. [53] | Disaster Scenarios | Multi-UAV | Optimization/Control | No | Sim | Task allocation accuracy, forecasting error |
| Qiu et al. [27] | General SAR | Cluster UAV | Distributed Control | No | HIL * | Computing complexity, payload endurance |
| Wu et al. [54] | Unknown Env. | UAV | DRL/MARL | No | Sim | Path planning time, conversion speed |
| Wu et al. [55] | General SAR | Drone Swarms | DRL/MARL | No | Sim | Detection capability, mission success |
| Wuwer et al. [56] | Transfer: MUM-T | UAV-Helicopter | Optimization/Control | Yes | Sim | Route efficiency, pilot cognitive workload |
| Xiong et al. [19] | Disaster Rescue | Multi-Drone | Metaheuristics | No | Sim | Assignment cost–revenue, path optimality |
| Yang et al. [57] | Indoor/Factory | Heterogeneous | Optimization/Control | No | Sim | Average path length, algorithm runtime |
| Yanmaz [24] | General SAR | Multi-UAV + relays | Optimization/Control | No | Sim | Target detection time, connectivity time |
| Yuan et al. [20] | Emergency Rescue | UAV Swarm | DRL/MARL | No | Sim | Recall, flight efficiency, bandwidth per step |
| Zhang et al. [58] | General SAR | Helicopter-UAVs | Metaheuristics | Yes | Sim | Task allocation efficiency, service cost |
| Zhang et al. [59] | Earthquake | Helicopter-UAVs | Metaheuristics | Yes | Sim | Total SAR time, site selection cost |
| Zhao et al. [60] | Cluttered Env. | Drone Swarms | DRL/MARL | No | Sim | Average speed, success rate, mission time |

* Note: Sim = Simulation; HIL = Hardware-in-the-Loop.

### 3.3. Algorithm Families and SAR Objectives

The literature demonstrates that drone SAR operations are fundamentally driven by two competing mission objectives: rapid area coverage (minimizing the time required to sweep a designated zone) and dynamic target localization (identifying and converging on specific victim signatures in cluttered environments). To achieve these objectives, researchers predominantly employ two distinct algorithmic families: bio-inspired metaheuristics and Deep Reinforcement Learning (DRL).

#### 3.3.1. Bio-Inspired Metaheuristics for Static Coverage

For rapid Coverage Path Planning (CPP) over large, static geographical grids, bio-inspired algorithms are widely favored for their low computational overhead and ability to balance swarm dispersion with target exploitation. Comparative evaluations within the literature indicate that Particle Swarm Optimization (PSO) generally yields superior exploration scores by maintaining balanced inter-drone separation, whereas pheromone-based models like Ant Colony Optimization (ACO) frequently suffer from premature convergence, leading to redundant flight paths over previously searched areas [42,59]. These comparative rankings are conditional rather than absolute. The PSO advantage has been demonstrated primarily on open, sparsely obstructed grids; in densely obstructed or corridor-constrained topologies, velocity-driven particles expend iterations rejecting infeasible moves, and pheromone-based methods may regain the advantage because stigmergic maps progressively encode feasible corridors, particularly when evaporation rates are raised ($\rho \approx 0.7$–$0.75$) to counter premature convergence [42]. Hybridization offers a further hedge: coupling PSO with grey-wolf ranking improved task-allocation cost and operation duration over either metaheuristic alone in post-earthquake scenarios [17], and genetic-algorithm assignment combined with sine–cosine PSO path planning performed comparably in 3D disaster terrain [19].

#### 3.3.2. Deep Reinforcement Learning (DRL) for Dynamic Adaptation

When the SAR objective shifts to navigating highly unstructured, dynamic 3D environments, DRL and Multi-Agent RL (MARL) emerge as the dominant frameworks [35,54]. Algorithms such as Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC) allow drone swarms to learn decentralized, cooperative exploration policies. To manage the massive computational overhead inherent to DRL, researchers optimize network architectures; for example, replacing fully connected layers with Convolutional Neural Networks (CNNs) has been shown to reduce model parameters by over 92%, enabling faster onboard execution for clustered drones navigating physical obstacles [60]. Furthermore, hybrid approaches have emerged to handle irregular search boundaries, such as coupling PPO with Mixed Integer Linear Programming (MILP) to minimize wasted flight time outside of designated polygonal search zones [38].

### 3.4. Algorithmic Mechanics, Hyperparameter Configurations, and Swarm Topologies

To transition the theoretical advantages of these algorithms into operational deployments, it is critical to evaluate their exact mathematical mechanisms, communication architectures, and optimal tuning parameters. The convergence stability, exploration speed, and communication overhead of a drone swarm are entirely dependent on how the underlying state–action spaces and bio-inspired heuristics are parameterized. Table 4 synthesizes the deep technical characteristics of the most prominent algorithms identified in the literature, providing a precise architectural baseline for reproducing and benchmarking future SAR models.

**Table 4.** Technical characteristics and hyperparameter configurations of state-of-the-art SAR algorithms.

| Algorithm & Core Studies | Swarm Communication Architecture | Constraint Handling & Limitations | Key Mathematical Mechanisms & Hyperparameters |
|---|---|---|---|
| **Proximal Policy Optimization (PPO)** [35,38] | **Decentralized (Dec-POMDP):** Agents share implicit rewards but maintain independent local action policies to reduce bandwidth. | **Strengths:** Adapts to highly irregular, non-convex boundaries and complex 3D topographies. **Limits:** High sample inefficiency during initial training phases. | **Objective:** Clipped surrogate objective function. **Hyperparameters:** Discount factor $\gamma$ = 0.90–0.99; clipping parameter $\varepsilon$ = 0.2; learning rate $\alpha$ = not specified; action standard deviation $\sigma$ = 0.2. |
| **Hierarchical Mapping-Partitioning DQN (HMPS)** [44] | **Attention-Weighted Flooding (AWF):** Messages are relayed based strictly on content relevance and link quality, avoiding network saturation. | **Strengths:** Highly resilient in GPS-denied areas and under severe communication bandwidth limitations. **Limits:** Discrete action spaces limit smooth multi-rotor kinematics. | **Objective:** Quadtree spatial partitioning combined with temporal-difference loss minimization. **Hyperparameters:** Adam optimizer learning rate $\alpha$ = not specified; discount factor $\gamma$ = 0.99; soft target update $\tau$ = 0.005; $\varepsilon$-greedy decay from 1.0 to 0.05; replay buffer = 50,000. |
| **Hierarchical Gradient Reward Q-Learning (HGR-QL)** [49] | **Hybrid (Dual-Layer):** Independent local Q-tables for real-time autonomy, synchronized every 10 steps with a regional shared Q-table. | **Strengths:** Explicitly handles dynamic wind interference and large-scale deployments (up to 300 UAVs) with latency 120 ms. | **Objective:** Multi-level gradient reward prioritizing target zones over local obstacle avoidance. **Hyperparameters:** Learning rate $\alpha$ = 0.1; discount factor $\gamma$ = 0.95; initial exploration rate $\varepsilon$ = 0.2; regional integration weight $\lambda$ = 0.3. |
| **Convolutional Soft Actor-Critic (CSAC)** [60] | **Implicit Visual/Radar Range:** Drones operate in a communication-denied zone; coordination relies entirely on mutual observation. | **Strengths:** Reduces model parameters by 92.91% compared to standard SAC, speeding up onboard execution in cluttered scenes. | **Objective:** Entropy maximization to prevent premature convergence and encourage aggressive exploration. **Hyperparameters:** Discount factor $\gamma$ = 0.99; batch size = 256; uses CNN feature extraction instead of fully connected neural networks (FCNNs). |
| **Particle Swarm Optimization (PSO)** [42,43] | **Distributed Tracking:** Swarm dynamically updates positions based on mathematical comparison of personal-best and global-best grid cells. | **Strengths:** Achieves minimal redundancy ratio (~0.25) while maintaining highly balanced 15–20 m inter-drone separation. **Limits:** Struggles with dynamic, moving targets. | **Objective:** Velocity-update vectors guided by a shared thermal Probabilistic Victim Map (PVM). **Hyperparameters:** Inertia weight $\omega$ = 0.9; cognitive coefficient $c_1$ = 1.5; social coefficient $c_2$ = 1.9. |
| **Ant Colony Optimization (ACO)** [42,59] | **Stigmergic (Pheromone-based):** UAVs read and deposit digital pheromones over a shared map to dictate route probability. | **Strengths:** Excellent for optimizing sequential waypoint routing from helicopter deployment carriers. **Limits:** High redundancy due to rapid pheromone convergence (exploitation over exploration). | **Objective:** Probabilistic path choice driven by pheromone deposition and evaporation rates. **Hyperparameters:** Pheromone importance $\alpha$ = 1.0; heuristic importance $\beta$ = 2.0–5.0; evaporation rate $\rho$ = 0.5–0.75. |

Analysis of Algorithmic Trade-Offs

The synthesis of these hyperparameter configurations reveals critical engineering trade-offs regarding computational overhead, swarm communication, and environmental adaptability.

**Communication vs. Processing Overhead.** Deep Reinforcement Learning (DRL) models such as PPO and SAC demonstrate strong adaptability in unknown, dynamic environments but incur substantial computational overhead. To mitigate this, state-of-the-art implementations are transitioning away from fully connected neural networks (FCNNs) and centralized critics. For example, Zhao et al. [60] demonstrated that utilizing Convolutional Neural Networks (CNNs) in a Soft Actor-Critic (CSAC) architecture can reduce algorithmic parameters by over 92% and trim decision times by 5.90%, making DRL viable for the size, weight, and power (SWaP) constraints of small quadrotors. Conversely, Khetal et al. [44] resolved bandwidth saturation through their Attention-Weighted Flooding (AWF) protocol, suggesting that drones may need to transmit only target-relevant features rather than continuous coordinate telemetry to maintain high coverage rates. Communication overhead and scalability differ measurably between these designs: AWF constrains message propagation by content relevance and link quality, sustaining coverage under severe bandwidth limits [44], whereas the dual-layer Q-table design bounds per-agent memory and synchronizes regionally every ten steps, maintaining a stable ≈100–120 ms communication delay at swarm sizes up to 300 UAVs [49]. A third design point compresses inter-agent messages to a fixed 64-byte mean-pooled feature vector per step, roughly two orders of magnitude below feature-sharing baselines, while retaining a 0.70 target recall [20]. Of the three, only the mean-pooling design reports an explicit communication-complexity scaling (quadratic-to-linear in the number of agents); the overhead of the other two designs must be extrapolated from the reported swarm sizes.

**Exploration vs. Exploitation in Metaheuristics.** While RL dominates dynamic adaptation, bio-inspired algorithms remain the benchmark for rapid, static-grid area coverage due to their minimal computational load. The literature explicitly confirms that parameter tuning dictates mission success. Kareem et al. [42] identified that Ant Colony Optimization (ACO), when constrained to standard evaporation rates ($\rho$ = 0.5), suffers from premature convergence, driving UAVs to exploit known paths and heavily increasing redundancy. In contrast, tuning Particle Swarm Optimization (PSO) with a high social coefficient ($c_2$ = 1.9) forces the swarm to actively space out (maintaining 15–20-m gaps), accelerating the coverage of unexplored thermal zones.

**Computational Complexity, Convergence, and Hardware Suitability.** The metaheuristic families scale approximately linearly per iteration with swarm and grid size, converge within hundreds of iterations, and run comfortably on microcontroller-class companion computers, which explains their persistence in SWaP-constrained SAR swarms [19,42]. Tabular Q-learning variants remain lightweight at run time, but their state–action tables grow combinatorially with grid resolution, growth that HGR-QL bounds through hierarchical decomposition [49]. Deep RL policies invert that profile: training is sample-hungry and typically performed off-board, while onboard inference cost depends on network compression; the 92.91% parameter reduction in the CNN-based CSAC is precisely what renders DRL feasible on small quadrotors [60]. Convergence evidence is empirical throughout: none of the reviewed studies provides formal convergence, robustness, or stability certificates for the disaster conditions it targets.

**Handling the "Collision Trap":** A significant operational risk in massive swarms is the "collision trap," in which UAVs prioritizing target discovery crowd into the same airspace, triggering cascading collision-avoidance halts [49]. Liu et al. [49] sought to address this through the Hierarchical Gradient Reward Q-Learning (HGR-QL) architecture. HGR-

QL penalizes collision proximity through a distance-decay gradient (−50 for imminent collision, −4 for minor detours) set against a +200 reward for reaching the primary target area. Reward shaping of that kind, however, biases behavior statistically while providing no separation guarantee: because the target reward dominates the collision penalty in magnitude, an agent may rationally accept collision risk in expected return, and shaped rewards yield neither a lower bound on separation distance nor a bound on violation probability. Formal assurance would instead require constructions such as potential-based shaping with a policy-invariance argument, control barrier functions, reachability analysis, or run-time shielding. Notably, no SAR swarm algorithm reviewed here provides formal separation assurance of that kind, a finding developed further in Sections 3.6 and 4.1.

By utilizing the parameters detailed in Table 4, future researchers may reduce reliance on the computationally expensive trial-and-error phases of algorithm design by drawing on these established baselines to test novel multimodal sensors or hardware-in-the-loop environments.

### *3.5. Reality-Gap Limitations and Sensor Fusion*

While the algorithmic math within the reviewed studies is mature, the synthesis reveals a recurring concern regarding how environmental constraints are modeled.

#### 3.5.1. The Static Survivor Fallacy

The vast majority of the synthesized path-planning literature assumes that targets remain stationary. When dynamic survivor mobility is introduced into swarm simulations (e.g., ambulatory victims seeking help), the effectiveness of traditional coverage algorithms drops significantly, necessitating a shift toward continuous, predictive target tracking rather than simple geometric area mapping [31,50].

#### 3.5.2. Sensing Uncertainty and False Positives

Idealized models frequently assume perfect target detection, ignoring the stochastic nature of thermal and visual sensing in environments obscured by smoke or dense canopy. Several studies address this through hierarchical dual-altitude architectures: high-altitude drones generate probabilistic thermal maps, prompting low-altitude drones to descend and execute YOLO-based visual confirmation, effectively filtering out non-human heat sources [43,46]. Furthermore, Bayesian filtering is increasingly applied to dynamically estimate and update the true sensitivity of the swarm's sensors over time as they perform subsequent passes over suspected coordinates [47].

#### 3.5.3. Communication Fragility

A foundational limitation in multi-agent swarm logic is the assumption of perfect data sharing. In physical disaster zones, communication is often degraded. Robust architectures utilize localized, hierarchical mechanisms, such as Attention-Weighted Flooding (AWF), to relay only highly relevant target features across the swarm [44], or dual-layer Q-tables that allow continuous local decision-making while stabilizing communication delays with regional swarm updates [49]. Bandwidth-aware message design is emerging as a third mitigation: fixed-length mean-pooled feature vectors bound per-agent messaging at 64 bytes per step in simulated emergency-rescue swarms while retaining a 0.70 target recall (Section 3.4) [20].

### *3.6. Deconfliction Assumptions in Mixed Airspace*

The synthesis identifies a stark divide between search optimization and airspace safety. The majority of SAR algorithms assume a sterile, conflict-free airspace, using implicit deconfliction (e.g., embedding collision-penalty gradients into an RL reward function) while entirely ignoring the presence of manned rescue assets [49]. Only a highly specialized subset of the literature addresses MUM-T and tactical deconfliction explicitly. Within this subset, crewed helicopters are integrated either as logistical constraints or cooperative traffic. The evidence base for RQ2 is thin: only six of the 44 included studies address crewed-aircraft deconfliction at all, and four of the six constitute transfer evidence from wildfire response, generic detect-and-avoid, non-cooperative threat avoidance, and manned–unmanned teaming rather than SAR-specific investigations. Conclusions regarding MUM-T in SAR are therefore tentative. Moreover, deconfliction in all six studies rests on procedural separation, shared telemetry, or reactive maneuvering rather than provable separation bounds.

#### 3.6.1. Strategic Carrier-Based Deconfliction

Deconfliction is achieved strategically by optimizing the UAV swarm's remote take-off and landing coordinates. Planners explicitly constrain the drones' geographic zones to prevent them from crossing the manned helicopter's airspace, significantly reducing collision risk while increasing search efficiency [59].

#### 3.6.2. Tactical Trajectory Planning

In concurrent operational models, tactical deconfliction relies on shared telemetry. By integrating Unmanned Aircraft System Traffic Management (UTM) protocols with manned helicopter management systems, autonomous scout UAVs can relay real-time 3D obstacle data to a helicopter's short-term trajectory planner, safely guiding the human pilot through low-level maneuvers without violating separation buffers [32,56].

As detailed in the preceding sections, Table 5 summarizes the explicit deconfliction approaches, surveillance sources, and airspace coordination strategies of these six relevant studies.

**Table 5.** Deconfliction and airspace safety mechanisms in included studies ($n$ = 6).

| Study | Crewed-Aircraft Involvement | Strategic or Tactical Method | Surveillance Source | Separation or Right-of-Way Logic | Conflict-Resolution Action | Validation Type |
|---|---|---|---|---|---|---|
| Andreeva-Mori et al. [32] | Yes (helicopter) | Strategic & Tactical | D-NET system/UTM shared telemetry | Shared volumetric area limits (UAS Volume) | Pilot identifies conflict via display and diverts | Flight Test |
| Mukherjee et al. [51] | No (simulated intruder) | Tactical | Simulated onboard sensors (e.g., ADS-B) | Explicit ICAO airborne right-of-way rules | Real-time model predictive control alters heading and speed | Simulation |
| Pradhan Shrestha et al. [53] | No (non-cooperative threat) | Tactical | Radar Field of View (FOV) | ICAO right-of-way & Inverse Proportional Navigation (IPN) | Cubic spline dynamic path planning & Monte Carlo prediction | Simulation |
| Wuwer et al. [56] | Yes (helicopter) | Tactical | Scout UAVs relaying 3D obstacle data | Shared telemetry and separation buffers | Helicopter trajectory planner safely guides pilot maneuvers | Simulation |
| Zhang et al. [58] | Yes (helicopter as carrier) | Strategic | Pre-flight mapping | Pre-calculated task allocation and hovering zones | Geographically separating UAV operating regions | Simulation |
| Zhang et al. [59] | Yes (helicopter as carrier) | Strategic | Pre-flight mapping | Task allocation restricting UAV airway crossings | Optimizing remote takeoff and landing coordinates | Simulation |

### *3.7. Validation Maturity and Evidence Strength*

The overarching strength of the synthesized evidence is defined by a high degree of mathematical rigor offset by low operational validation maturity. Across the included studies, approximately 86% (38 out of 44) validated their proposed SAR and deconfliction algorithms exclusively in idealized computer simulations. These simulated environments frequently abstract away the non-linear battery drain caused by severe wind shear, rotor downwash, and the aerodynamic penalties of aggressive collision avoidance.

Consequently, while preliminary evidence suggests that autonomous swarms may outperform human-assisted teams in minimizing time-to-first-detect under simulated conditions [35], the certainty of evidence regarding operational translation remains limited. Only a fraction of the literature advances to HIL experimental validations or physical field flight tests [15,18,27,32,43,45]. The synthesized data indicate that, while the field has reported substantial algorithmic progress in coverage path planning and reinforcement learning, the discipline should transition to physical benchmarking to demonstrate resilience to the dynamic constraints of real-world disaster airspace. Notably, two of the four flight-validated studies entered through the supplementary search: cooperative search-and-coverage control developed in simulation and then demonstrated on physical quadcopters in a post-earthquake assessment scenario [15], and an end-to-end deep-reinforcement-learning SAR system flight-tested on physical quadrotors in a GNSS-denied disaster mock-up, where it won the 2024 NATO-Sapience Autonomous Cooperative Drone Competition [18]. Both demonstrate that simulation-to-reality transfer is achievable when it is prioritized from the outset.

## 4. Discussion

### *4.1. Synthesis of Key Findings*

The primary objective of this systematic literature review was to synthesize the state of the art in autonomous unmanned aerial vehicle (UAV) search-and-rescue (SAR) optimization and to evaluate how autonomous swarms achieve tactical deconfliction in mixed manned–unmanned airspace. The synthesized literature indicates a notable directional shift in disaster response: centralized, manually piloted individual drones are increasingly being replaced by decentralized, autonomous swarms driven by Deep Reinforcement Learning (DRL) and bio-inspired metaheuristics.

Regarding the optimization of coverage path planning (CPP) and task allocation, the reviewed evidence suggests that autonomous swarms tend to outperform traditional human ground teams and manually piloted UAVs in minimizing time-to-first-detect under simulated conditions. For example, Bialas et al. [35] reported through empirical benchmarking that multi-agent Proximal Policy Optimization (PPO) algorithms navigated 3D environments faster than human-assisted flights. However, this direct human-versus-swarm comparison rests largely on a single study. Moreover, the literature indicates that optimized pathing is only half the solution; successful SAR operations require highly reliable semantic target localization to prevent wasted rescue efforts due to false positives. The integration of dual-altitude, multi-modal sensing, such as deploying high-altitude UAVs for thermal probabilistic mapping followed by low-altitude UAVs for YOLO-based visual confirmation [43], appears to be a promising architectural approach for balancing rapid area coverage with high classification accuracy.

Furthermore, this review highlights a critical but historically under-researched intersection: the coupling of SAR optimization with tactical airspace deconfliction. The literature indicates that real-world disaster zones are not exclusively drones' domain; rather, they are chaotic, low-altitude airspace shared with crewed rescue helicopters. The findings reveal that effective MUM-T requires treating deconfliction not as a separate air traffic control problem, but as a core constraint within the SAR optimization loop itself. Architectures that optimize remote take-off and landing points for carrier helicopters explicitly prevent swarm trajectories from crossing manned flight paths [59], while adaptive short-term trajectory planners ensure safe low-level helicopter flight alongside scout UAVs [56]. Thus, a key indicator of a modern SAR algorithm's effectiveness is its ability to concurrently maximize search coverage while maintaining dynamic separation buffers against crewed assets and non-cooperative obstacles. Framed as a negative result, the strongest RQ2 finding of the present review is that no reviewed SAR swarm algorithm provides formally assured separation: reward-shaped penalties, geographic partitioning, and telemetry sharing all reduce conflict likelihood, but none yields a provable separation lower bound or violation-probability guarantee of the kind that certification in mixed airspace will ultimately demand.

### *4.2. Limitations of the Evidence: The Reality Gap*

Despite notable algorithmic progress, a review of the included literature reveals a recurring gap between the assumptions of mathematical models and the conditions of operational deployment. Most current SAR optimization models rely on assumptions that immediately break down in physical disaster zones. Divergences are summarized in Figure 4.

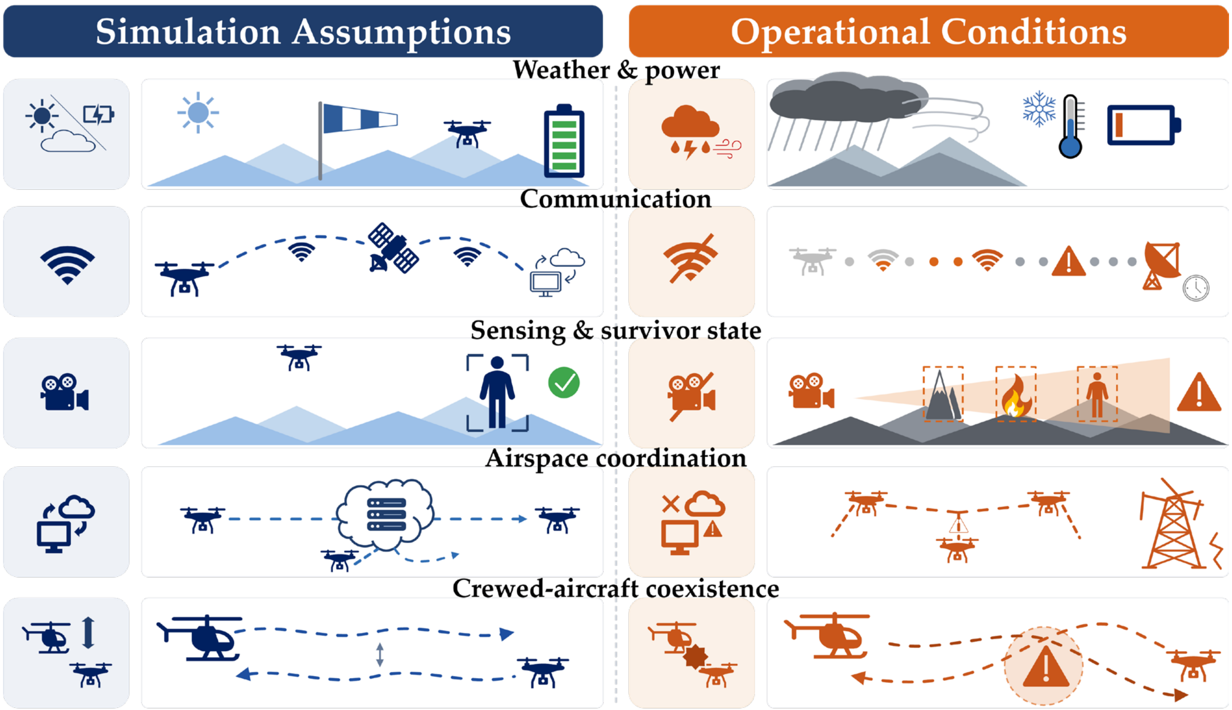


**Figure 4.** The simulation-to-operation reality gap in drone-based SAR. Idealized simulation assumptions (**left**) are contrasted with operational conditions (**right**) across weather and power, communication, sensing, airspace coordination, and crewed-aircraft coexistence; the transfer gap marks the validation distance separating the two.

#### 4.2.1. The Simulation Bias

The most prominent limitation is the overwhelming reliance on idealized computer simulations. As observed in the study characteristics, approximately 86% (38 out of 44) of the included studies validated their algorithms exclusively in software (e.g., Gazebo, AirSim). These environments frequently abstract away the nonlinear battery drain caused by severe wind shear, rotor downwash, and the aerodynamic penalties of aggressive obstacle avoidance. The metric census (Section 3.2 and Table A2) sharpens the concern: explicit energy or endurance metrics appear in only two of the 44 included studies, so the field's energy-efficiency discourse rests almost entirely on unmeasured simulation assumptions; until algorithms undergo rigorous HIL testing and field trials with instrumented power measurement, energy claims remain effectively unvalidated.

Three structural drivers explain the persistence of the simulation bias. First, physical trials carry costs and regulatory burdens that scale steeply: multi-aircraft beyond-visual-line-of-sight operations in unstructured terrain require airspace approvals, certified remote pilots, and safety cases that few research groups can sustain. Second, the field lacks standardized physical benchmarks and shared testbeds, so no publication incentive rewards the expensive replication of a competitor's field conditions; a recent benchmarking framework is a first corrective step [35]. Third, funding and publication cycles reward algorithmic novelty over validation maturity, making a new optimizer in simulation a faster path to publication than a field campaign with an existing one. Closing the gap therefore requires shared testbeds, benchmark scenarios, and minimum reporting standards (Table A3).

#### 4.2.2. The Static Survivor Fallacy

The vast majority of coverage and task allocation algorithms assume that once a disaster occurs, victims remain stationary. This assumption fundamentally compromises search efficiency. Mather et al. [50] demonstrated that swarm effectiveness drops drastically when survivors are ambulatory (e.g., wandering or seeking help). Algorithms that treat SAR as a static mapping problem will fail to account for targets moving out of previously searched grid cells, necessitating a shift toward dynamic, predictive tracking models [31]. The reviewed evidence suggests three adaptation paths. First, recursive state estimation, in which Kalman-family or particle filters propagate an explicit survivor motion state (as applied to maritime target tracking [31]), can replace static occupancy grids with predicted-position distributions. Second, Bayesian re-weighting of previously searched cells [47] counteracts the erroneous certainty that a swept cell remains empty when survivors are ambulatory. Third, learned motion models trained on lost-person behavior statistics could condition the search prior on terrain and survivor profile; no reviewed study yet implements such a model, which marks a concrete research opening rather than a solved problem.

#### 4.2.3. Communication Fragility and Sensing Uncertainty

A foundational flaw in many multi-agent reinforcement learning (MARL) models is the assumption of perfect, instantaneous data sharing across the swarm. Post-disaster environments are inherently communication-denied. While notable exceptions exist, such as Liu et al. [49] stabilizing communication delays using hierarchical Q-tables, and Horyna et al. [41] designing swarms that operate without explicit radio communication by relying on relative visual localization, most models fail to simulate severe packet loss or latency. Furthermore, the reliance on idealized sensor data ignores the stochastic nature of thermal and visual sensing in environments obscured by smoke, fire, or dense canopy, a gap that necessitates continuous Bayesian sensitivity estimations to quantify detection confidence over time [47].

### *4.3. Reporting and Methodological Appraisal of Included Studies*

The methodological quality and reporting transparency of the 44 included studies were appraised using an 8-item, MMAT-informed engineering checklist. Of the 44 studies, 42 (95%) achieved a consensus rating of "Low Concern" for reporting transparency and methodological formulation (defined as a consensus score $\geq$ 75% with at most one "no" rating); two studies [21,23] were rated "Some Concern", principally for single-baseline comparisons and limited treatment of uncertainty. These ratings reflect the transparency of reporting and the methodological rigor of the included studies. The final consensus scores for each study, derived through item-by-item adjudication across three independent reviewers, are presented in Table 6. Two qualifications bound the interpretation of the result. First, the instrument measures reporting transparency and methodological formulation only; it is orthogonal to operational validation maturity, which is assessed separately in Section 3.7. A study can therefore transparently report an idealized simulation, scoring "Low Concern", while still exemplifying the reality gap the review critiques. Second, the aggregate rating compresses item-level variation. Table 7 therefore reports the item-level consensus distribution: whereas formulation items 1, 2, 3, and 5 are satisfied almost universally and item 4 by 34 of 44 studies, only 18 of 44 studies fully satisfied item 6 (operational realism), only 12 of 44 fully satisfied item 7 (treatment of uncertainty, latency, packet loss, degraded communications, platform failure, and sensing limitations), and only 25 of 44 fully satisfied item 8 (validation maturity and reproducibility). The item-level evidence thus independently corroborates the reality-gap findings of Sections 3.7 and 4.2 from within the appraisal data itself.

**Table 6.** Reporting and methodological quality appraisal consensus scores ($n$ = 44).

| Study | R1 | R2 | R3 | Cons. | Study | R1 | R2 | R3 | Cons. |
|---|---|---|---|---|---|---|---|---|---|
| Abdellatif et al. [28] | 88 | 81 | 100 | **94** | Khetal et al. [44] | 81 | 88 | 100 | **88** |
| Aggarwal et al. [29] | 88 | 88 | 75 | **94** | Kopyt & Czaplińska [45] | 69 | 88 | 81 | **88** |
| Al-Husseini et al. [30] | 100 | 88 | 100 | **100** | Leong [46] | 31 | 94 | 100 | **94** |
| Aminzadeh & Khoshnood [15] | 56 | 88 | 94 | **88** | Lima et al. [47] | 38 | 75 | 94 | **75** |
| Anastasiou et al. [31] | 69 | 75 | 88 | **81** | Liu et al. [48] | 94 | 81 | 81 | **94** |
| Andreeva-Mori et al. [32] | 69 | 75 | 94 | **81** | Liu et al. [49] | 94 | 81 | 100 | **94** |
| Bassolillo et al. [33] | 75 | 94 | 88 | **88** | Ma et al. [22] | 88 | 81 | 88 | **88** |
| Bernardo et al. [34] | 69 | 81 | 94 | **81** | Mather et al. [50] | 94 | 81 | 88 | **94** |
| Bialas et al. [35] | 88 | 81 | 100 | **88** | Mukherjee et al. [51] | 81 | 69 | 88 | **75** |
| Chen et al. [36] | 56 | 88 | 88 | **88** | Pradhan Shrestha et al. [53] | 81 | 88 | 100 | **88** |
| Chin et al. [37] | 75 | 88 | 88 | **88** | Pu et al. [52] | 94 | 81 | 94 | **88** |
| Cho et al. [21] | 50 | 69 | 81 | **69** | Qiu et al. [27] | 69 | 81 | 88 | **81** |
| Choi et al. [38] | 94 | 81 | 88 | **94** | Wu et al. [54] | 94 | 81 | 88 | **94** |
| Du [23] | 56 | 63 | 94 | **69** | Wu et al. [55] | 81 | 81 | 88 | **81** |
| Gracia Otalvaro & Watson [39] | 63 | 81 | 88 | **88** | Wuwer et al. [56] | 31 | 88 | 94 | **81** |
| Haddad et al. [16] | 63 | 81 | 94 | **81** | Xiong et al. [19] | 69 | 75 | 88 | **81** |
| Han et al. [17] | 44 | 81 | 81 | **75** | Yang et al. [57] | 88 | 81 | 100 | **88** |
| He et al. [40] | 56 | 88 | 100 | **88** | Yanmaz [24] | 81 | 81 | 100 | **81** |
| Hickling et al. [18] | 69 | 94 | 100 | **94** | Yuan et al. [20] | 56 | 88 | 94 | **88** |
| Horyna et al. [41] | 81 | 100 | 75 | **94** | Zhang et al. [58] | 100 | 88 | 100 | **100** |
| Kareem et al. [42] | 75 | 81 | 100 | **81** | Zhang et al. [59] | 100 | 81 | 94 | **94** |
| Kareem et al. [43] | 94 | 81 | 100 | **94** | Zhao et al. [60] | 88 | 81 | 94 | **88** |

Note. Percentages are based on the eight-item modified MMAT-informed checklist described in Section 2.5. Consensus scores were not calculated by arithmetically averaging the reviewers' total percentages. Instead, consensus was reached through strict item-level adjudication and discussion; the final percentage reflects the aggregated score of these individually agreed-upon items. R1 = Reviewer 1; R2 = Reviewer 2; R3 = Reviewer 3. The ten supplementary-search studies were appraised under the identical procedure (Section 2.5). Studies are ordered alphabetically by first author; the left block lists the first 22 studies and the right block the remaining 22. All values are percentages.

**Table 7.** Item-level consensus rating distribution across the eight appraisal items ($n$ = 44).

| Appraisal Item (Abridged from Section 2.5) | Yes | Partly | No |
|---|---|---|---|
| 1. Objective or research question clearly stated | 44 | 0 | 0 |
| 2. Method described in sufficient detail | 41 | 3 | 0 |
| 3. Method appropriate for the stated problem | 44 | 0 | 0 |
| 4. Comparators, baselines, or benchmarks adequate | 34 | 9 | 1 |
| 5. Metrics clearly defined and mission-aligned | 44 | 0 | 0 |
| 6. Scenarios operationally realistic | 18 | 26 | 0 |
| 7. Uncertainty, latency, packet loss, degraded communications, platform failure, or sensing limits addressed | 12 | 29 | 3 |
| 8. Validation maturity adequate; reproducibility judgeable | 25 | 19 | 0 |

Note. Item-level consensus ratings were derived by majority rule across the three reviewers for all 44 included studies, with the median rating used when all three differed. Items 6–8 are precisely the domains in which the reality gap documented in Sections 3.7 and 4.2 manifests.

Although 42 of the 44 studies met the threshold for low concern, these aggregate scores should be interpreted as indicators of reporting and methodological quality rather than field readiness. Operational validation was assessed separately using the study-level classifications reported in Section 3.7: 38 studies (86%) used software simulation exclusively, two (5%) incorporated hardware-in-the-loop testing, and four (9%) included flight or physical experimental testing.

### *4.4. Limitations of the Review Process*

While this review adhered strictly to PRISMA 2020 guidelines, certain methodological limitations must be acknowledged. First, the search strategy was confined to three major engineering databases (IEEE Xplore, AIAA Aerospace Research Central, and Web of Science) and restricted to English-language, peer-reviewed literature. Consequently, relevant gray literature, such as technical white papers from aviation authorities (e.g., FAA, EASA) or field reports from active emergency management agencies (e.g., FEMA), was excluded. A subsequent targeted supplementary search broadened keyword and publisher coverage (Section 2.2), partially mitigating the database-coverage limitation, although the supplementary search was restricted to Scopus and gray literature remains outside the review's scope.

Second, the strict exclusion of general Unmanned Traffic Management (UTM) and Urban Air Mobility (UAM) studies was necessary to maintain a deep focus on disaster assistance and low-altitude SAR. However, this rigorous filtration may have omitted generalized multi-agent collision-avoidance algorithms or urban delivery routing protocols that could theoretically be adapted to SAR applications, even if the original authors did not explicitly test them in a rescue context.

### *4.5. Implications for Practice, Policy, and Future Research*

The findings of this review offer highly actionable implications for aerospace engineers, emergency response coordinators, and regulatory policymakers.

#### 4.5.1. Implications for Practice and Policy

For SAR commanders, the reviewed evidence suggests a shift away from deploying single, manually operated drones toward heterogeneous, dual-altitude swarms that fuse thermal and visual data at the edge [28,43]. From a policy perspective, the integration of UAV swarms into active disaster airspace underscores the need for updated aviation separation standards. Current Right-of-Way (RoW) rules must be codified into the drones' autonomous decision-making logic [51]. Regulators must facilitate frameworks that enable decentralized, tactical DAA maneuvers rather than relying solely on strategic, pre-flight airspace reservations, which are entirely impractical in chaotic, time-critical rescue scenarios.

#### 4.5.2. Directions for Future Research

To successfully transition autonomous drone swarms from the laboratory to the field, future research should systematically address the "reality gap."

1. Dynamic Reward Functions: Future DRL models must transition away from static mission parameters. Researchers should explore integrating Large Language Models (LLMs) as meta-agents to dynamically update reinforcement learning weights based on real-time environmental reports [55] and embedding entropy-maximizing algorithms such as Soft Actor-Critic (SAC) to encourage robust exploration in unknown obstacle fields [39].
2. Coupling Path Planning with Deconfliction: The siloed nature of SAR research should evolve. Future optimization models should natively fuse coverage path planning with real-time tactical deconfliction algorithms. Planners must model non-cooperative

dynamic threats, such as moving debris or rogue drones [53], directly into the swarm's local obstacle avoidance calculations.

3. Standardized Benchmarking: To allow for true comparative analysis, the research community must adopt standardized physical benchmarks. Future studies should adopt the minimum reporting checklist provided in Table A3, which recasts the appraisal items of Section 2.5 in imperative form and extends them with operationally critical elements the appraisal instrument did not capture: an explicit wind/gust disturbance model, numerical separation thresholds, computational-cost reporting, a declared simulation-fidelity level (incorporated in item 8), and open code and data availability.

While advanced AI and optimization frameworks have demonstrated strong simulation performance against the constraints of the "Golden 72 Hours", the next era of UAV search-and-rescue research should prioritize the resilient, physical execution of these algorithms in mixed, chaotic, and environmentally demanding airspace.

## 5. Conclusions

The present systematic literature review synthesized 44 core studies to evaluate the intersection of autonomous unmanned aerial vehicle (UAV) swarm optimization, multi-modal target localization, and tactical airspace deconfliction in low-altitude Search and Rescue (SAR) operations. The findings indicate a consistent trend toward autonomous, decentralized approaches in post-disaster response: traditional manual drone piloting is increasingly being supplemented or replaced by autonomous swarms driven by Deep Reinforcement Learning (DRL) and bio-inspired metaheuristics. Algorithms such as Proximal Policy Optimization (PPO), Soft Actor-Critic (SAC), and Particle Swarm Optimization (PSO) have shown promise in minimizing coverage path planning (CPP) times in complex, unstructured 3D terrains, outperforming human-assisted ground teams under simulated conditions and reducing the time-to-first-detect.

Furthermore, the synthesis demonstrates that optimal routing must be coupled with robust, multi-modal sensing to be operationally viable. The integration of dual-altitude architectures, in which high-altitude UAVs generate probabilistic thermal maps and low-altitude UAVs descend to perform YOLO-based visual confirmation, may help mitigate the false-positive limitations of single-sensor systems in cluttered environments.

However, the most significant barrier to the real-world deployment of such advanced swarms is their safe integration into mixed manned–unmanned airspace. Disaster zones are chaotic environments actively occupied by crewed rescue helicopters. The literature confirms that effective MUM-T requires treating deconfliction as a tactical necessity rather than a strategic traffic management problem. Models that optimize remote take-off and landing points to prevent UAVs from crossing helicopter flight paths, coupled with adaptive low-level trajectory planners that share situational awareness between human pilots and autonomous scouts, provide the architectural foundation for safe, concurrent airspace operations.

Despite the algorithmic progress documented in the reviewed studies, a recurring gap persists between simulation performance and operational readiness. Approximately 86% (38 out of 44) of the evaluated optimization models were validated exclusively in idealized computer simulations. Such environments frequently fail to account for the constraints of physical disaster zones, including dynamic survivor mobility, wind shear, and communication-denied conditions. To advance toward operational use within the "Golden 72 Hours" of disaster response, future research should shift from simulated benchmarks to HIL testing and field trials. The next generation of SAR drone swarms should integrate real-time tactical deconfliction, multi-modal sensor noise estimation, and decentralized communication resilience into their core optimization loops to operate safely alongside human responders in demanding environments.

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## Appendix A

**Table A1.** Exclusion reasons for records removed during full-text screening ($n$ = 81).

| **Exclusion Category** | **Reason** | ***n*** |
|---|---|---|
| Scope mismatch | Generic UTM, UAM, or high-altitude civil aviation integration with no SAR focus | 20 |
| Background/Context only | The paper lacked a novel algorithm or model, but was retained for background and literature review | 19 |
| Population mismatch | Not about unmanned aircraft or outside the target population | 12 |
| Human factors focus | Primary focus on human factors or operator interaction rather than SAR optimization or deconfliction | 7 |
| Research-question mismatch | Insufficient direct relevance to the three research questions | 5 |
| Application mismatch | Addressed low-altitude flight but not in a search, rescue, or disaster-response context | 4 |
| Limited deconfliction relevance | UAV-only collision avoidance with no manned-aircraft, ADS-B, DAA, or UTM context | 4 |
| Technical-domain mismatch | Addressed SAR but focused purely on sensor hardware or communications layer without a path-planning algorithm | 3 |
| Terminology mismatch | Used “SAR” as an acronym for unrelated concepts (e.g., Synthetic Aperture Radar) without a search and rescue context | 3 |
| Non-technical focus | Editorial, commentary, or high-level policy review without extractable engineering models | 2 |
| Full-text duplicate | Duplicate record discovered during the full-text review phase | 1 |
| Study-design mismatch | Lacked an extractable methodology, validation type, or performance metrics | 1 |
| Total Excluded | | 81 |

**Table A2.** Headline-metric frequency across included studies ($n$ = 44; categories are not mutually exclusive).

| Headline Metric Category | Studies ($n$) | Example Studies |
|---|---|---|
| Search, mission, or rescue time | 14 | Bernardo et al. [34]; Choi et al. [38]; Zhang et al. [59]; Han et al. [17] |
| Detection, localization, or tracking performance | 12 | Kareem et al. [43]; Leong [46]; Yuan et al. [20] |
| Task-completion or success rate | 6 | Liu et al. [49]; Zhao et al. [60]; Hickling et al. [18] |
| Path length or efficiency | 7 | Aggarwal et al. [29]; Yang et al. [57]; Xiong et al. [19] |
| Computational runtime, latency, or complexity | 7 | Wu et al. [54]; Qiu et al. [27] |
| Safety, separation, or conflict resolution | 5 | Mukherjee et al. [51]; Pradhan Shrestha et al. [53]; Andreeva-Mori et al. [32] |
| Coverage, exploration, or redundancy | 5 | Kareem et al. [42]; Khetal et al. [44]; Aminzadeh & Khoshnood [15] |
| Communication bandwidth or delay | 5 | Abdellatif et al. [28]; Yuan et al. [20] |
| Cost or resource use | 4 | Zhang et al. [58]; Chin et al. [37]; Han et al. [17] |
| Energy or endurance | 2 | Qiu et al. [27]; Haddad et al. [16] |

Note. Counts reflect the headline Key Metrics column of Table 3; several studies report metrics in more than one category.

**Table A3.** Minimum reporting checklist for future SAR swarm optimization and deconfliction studies.

| # | Reporting Item (Imperative Form) |
|---|---|
| 1 | State the study objective and the SAR mission profile addressed. |
| 2 | Describe the UAV platform(s), swarm size, and autonomy architecture in reproducible detail. |
| 3 | Justify the selected optimization or deconfliction method against the stated problem. |
| 4 | Report comparators and baselines, including at least one established method. |
| 5 | Define all performance metrics; report search/mission time and energy consumption wherever feasible. |
| 6 | Specify scenario realism: terrain, obstacles, day/night conditions, and airspace occupancy, including any crewed traffic. |
| 7 | Model and report degraded conditions: communication latency and packet loss, sensor noise and false-positive rates, and platform-failure handling. |
| 8 | Declare the validation tier (pure simulation, HIL, tethered or field flight) and the simulation-fidelity level (kinematic, dynamic, physics-engine, digital twin). |
| 9 | Include an explicit wind/gust disturbance model, or state its absence as a limitation. |
| 10 | Report numerical separation thresholds and right-of-way logic for all modeled traffic, crewed and uncrewed. |
| 11 | Report computational cost: training budget, onboard inference time, and per-agent communication overhead. |
| 12 | Provide open code and data, or state the barrier preventing release. |

Note. Items 1–8 recast the Section 2.5 appraisal domains imperatively, with item 8 adding the declared simulation-fidelity level; items 9–12 add the further elements identified in Section 4.5.2 (wind/gust modeling, numerical separation thresholds, computational-cost reporting, and open code and data availability).

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