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Swarm algorithms for UAV route planning: a systematic review of characteristics, classification, and operational performance

Algoritmos de enjambre para planificación de rutas en UAV: Una revisión sistemática de características, clasificación y desempeño operativo

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Abstract

Path planning for unmanned aerial vehicles (UAVs) using swarm algorithms is a central topic in autonomous robotics. However, the literature still lacks systematic reviews that jointly address algorithm classification, operational characteristics, and performance evaluation. This study proposes a five-category taxonomy, a domain-based frequency analysis, and a nine-metric evaluation framework. Following PRISMA guidelines, searches were conducted in IEEE Xplore, Scopus, ScienceDirect, and ACM Digital Library between November and December 2025. From an initial set of 2,761 records, 31 articles were included, comprising 25 primary studies and 6 systematic reviews. PSO, ACO, and ABC account for 66% of the 56 identified algorithm appearances, with prominent applications in defense, search and rescue, and agriculture. Hybrid methods emerged as the main research trend, while AI-based approaches show the greatest potential for scalability and autonomous adaptation. The reviewed literature prioritizes path length (96%) and convergence time (88%), whereas energy efficiency (56%) and area coverage (48%) remain comparatively underexplored.

Keywords: UAVs, swarm intelligence, path planning, metaheuristic optimization, PRISMA.

Resumen

La planificación de rutas para UAV mediante algoritmos de enjambre es clave en la robótica autónoma; sin embargo, faltan revisiones sistemáticas que integren clasificación, características operativas y desempeño. Este estudio propone una taxonomía de cinco categorías, un análisis de frecuencias por dominio y un marco de evaluación con nueve métricas. Siguiendo la metodología PRISMA, se revisaron las bases de datos IEEE Xplore, Scopus, ScienceDirect y ACM Digital Library entre noviembre y diciembre de 2025. De 2761 registros, se incluyeron 31 artículos: 25 estudios primarios y 6 revisiones. Los algoritmos PSO, ACO y ABC concentran el 66 % de las 56 implementaciones identificadas, con especialización en defensa, búsqueda y rescate, y agricultura. Los métodos híbridos constituyen la principal tendencia, mientras que la IA destaca por su potencial de escalabilidad y adaptación. La literatura prioriza la longitud de trayectoria (96 %) y el tiempo de convergencia (88 %), mientras que la eficiencia energética (56 %) y la cobertura de área (48 %) reciben menor atención.

Palabras clave: UAV, inteligencia de enjambre, planificación de rutas, optimización metahurística, PRISMA

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1. Introduction

1.1. Context and Motivation

Unmanned aerial vehicles (UAVs) have expanded rapidly across civil and military sectors because of their relatively low cost, operational flexibility, and ability to access remote or hazardous environments [1, 2]. They are now widely used in reconnaissance, precision agriculture, infrastructure inspection, disaster response, and emergency support, where rapid deployment and real-time information are essential for decision-making [3–5]. Technological advances have also enabled the development of UAV swarms, defined in this study as systems composed of two or more UAVs that coordinate through centralized or decentralized mechanisms to accomplish a shared mission [6]. Their scalability makes them particularly suitable for surveillance, search and rescue, environmental monitoring, and communication support in uncertain environments.

Path planning is a core challenge because UAVs must generate safe and efficient trajectories while satisfying constraints related to distance, threats, energy consumption, time windows, coverage, and admissible airspace [3], [7, 8]. In swarms, this becomes a coordination problem: vehicles must avoid collisions, route overlap, resource waste, and communication bottlenecks while acting cooperatively [6], [9].

Path-planning approaches comprise graph-based, swarm-based, and AI-based methods [5, 6]. Traditional algorithms, including Dijkstra and A*, perform well in structured settings, whereas swarm algorithms such as PSO, ACO, and ABC are better suited to dynamic multi-UAV optimization because they support population-based search, adaptability, and decentralized coordination [6], [10].

However, core swarm methods also have limitations: PSO may converge prematurely, ACO may scale poorly because of pheromone updates, and ABC may stagnate during exploitation [11]. These limitations explain the recent shift toward hybrid and AI-augmented approaches, underscoring the need for a structured synthesis of algorithm types, operational characteristics, and application-specific trade-offs.

1.2. Theoretical Framework and Related Work

Swarm intelligence is a computational paradigm inspired by decentralized biological systems in which local interactions generate adaptive collective behavior [12,13]. Its main principles include self-organization, local communication or stigmergy, feedback, and redundancy, which together provide robustness and adaptability in dynamic environments [13]. Among the foundational algorithms, ACO models pheromone-based foraging, PSO models flocking behavior, and ABC models bee foraging. These algorithms remain the principal reference methods in UAV path planning [14–16]. Later proposals, such as GWO, WOA, and SSA, have broadened the bio-inspired repertoire, particularly for high-dimensional optimization; however, the present review shows that these newer techniques remain less frequently validated in UAV-specific contexts [17–20].

Swarm algorithms are attractive because they explore multiple regions of the search space simultaneously, do not require gradient information, and adapt well to nonlinear or non-differentiable problems [21, 22]. These properties have supported applications in robotics, routing, and autonomous coordination and have encouraged recent work on hybridization with reinforcement learning and other AI methods for dynamic multi-agent settings [23–25].

Recent reviews address either general UAV path planning or swarm intelligence more broadly [26–29], but they do not jointly examine swarm-algorithm prevalence, taxonomic structure, operational characteristics, and comparative metrics for UAV path planning. This review addresses that gap by focusing on studies published between 2020 and 2025.

1.3. Problem Statement and Justification

Despite significant advances in the development of swarm algorithms for path planning, there remains a notable lack of systematic reviews that comprehensively integrate and classify algorithmic approaches, operational characteristics, and comparative performance across diverse application scenarios [30, 31].

Classical methods such as PSO, ACO, and ABC remain effective, but each has limitations in dynamic and complex scenarios [11]. This has driven the development of hybrid methods, yet the field still lacks unified evaluation metrics and common comparison protocols.

In this review, operational performance encompasses computational indicators, including convergence time, solution quality, and efficiency, as well as mission-level indicators, such as energy efficiency, area coverage, success rate, and threat exposure. This broader definition is necessary because UAV path planning must be evaluated beyond isolated optimization scores.

Accordingly, this PRISMA-based review synthesizes, classifies, and analyzes swarm algorithms for UAV path planning to support algorithm selection, identify research trends, and highlight future directions based on 25 primary studies and 6 prior reviews published between 2020 and 2025.

1.4. Research Objectives and Research Questions

Building on the gaps identified in the literature, this systematic review is structured around three interrelated research axes. The first seeks to determine which swarm algorithms are most frequently implemented in UAV path planning, using quantitative analysis to characterize the current landscape of the field and its dominant approaches. The second develops a grounded taxonomy that classifies these algorithms according to their theoretical foundations, optimization mechanisms, and coordination strategies, thereby providing an organizational framework for the diversity of existing approaches. Finally, the third examines the operational characteristics that define the behavior of these algorithms, ranging from multi-agent coordination to computational efficiency, and analyzes how these characteristics affect performance across different application contexts.

The main contributions of this work are threefold: (1) a five-category grounded taxonomy of swarm methods for UAV path planning, organized according to optimization and coordination strategies and developed empirically from patterns identified across 25 primary studies and theoretically from prior systematic reviews [26, 28, 27, 29] to provide an overarching organization of the diverse approaches found in the literature; (2) a quantitative assessment of 56 algorithm implementations across 25 studies, identifying the predominant methodologies used in each application domain, including defense (36.0%), search and rescue (32.0%), agriculture (20.0%), and inspection (8.0%), as well as their functional specialization; (3) a nine-metric evaluation framework for assessing swarm-method performance, with complete traceability to all reviewed studies, enabling systematic comparison across different approaches.

The remainder of this article is organized as follows: Section 2 details the PRISMA methodology employed; Section 3 presents the results and discussion; and Section 4 outlines the conclusions, limitations, and future research directions.

2. Materials and Methods

2.1. Systematic Review Strategy and Design

This systematic review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and replicability throughout the identification, selection, and analysis of studies [32].

Identification: The bibliographic search was conducted between November 15 and December 19, 2025, in four major academic databases selected for their relevance to robotics, artificial intelligence, and autonomous systems: ACM Digital Library, IEEE Xplore, ScienceDirect, and Scopus. The search was performed using the standardized search string defined in Section 2.2, with adaptations to the syntax requirements of each database interface while preserving semantic equivalence.

Screening: At this stage, duplicate records were identified through Mendeley Reference Manager's automatic detection feature based on DOI, title, and author matching. No duplicates were detected across the four databases, likely because of the specificity of the search string and the distinct coverage scope of each database. Subsequently, records with no direct relation to the research question, based on their title and abstract, were independently screened by the three authors, with disagreements resolved through discussion until consensus was reached. Reference management and bibliographic tracking were performed using Mendeley Reference Manager, while the screening matrix and data extraction were documented in shared spreadsheets using Google Sheets to ensure transparency and traceability.

Eligibility: Full-text assessment was applied to 51 preselected articles using the inclusion and exclusion criteria described in Section 2.3. Twenty studies were excluded mainly because they lacked swarm coordination, adequate metrics, temporal fit, or experimental/simulation-based validation.

Inclusion: The final selection comprised 31 articles that met all defined criteria. These studies were analyzed in depth to extract algorithmic implementations, operational characteristics, evaluation metrics, and application domains. The final corpus consisted of 25 primary studies on specific implementations of swarm algorithms and 6 systematic reviews that provided the theoretical framework for the proposed taxonomy.

2.2. Search String

A structured search string was developed by combining terms related to three main dimensions of the study: ("drone swarm" OR "swarm intelligence") AND ("route optimization" OR "path planning") AND ("algorithms" OR "optimization techniques").

The search string was designed to capture articles that simultaneously addressed three mandatory dimensions: (1) drone swarm systems, (2) route planning or optimization problems, and (3) algorithmic solutions. All searches were restricted to the 2020–2025 publication window and limited to journal articles and conference proceedings.

It is acknowledged that the search string may not capture all relevant studies, particularly those using nonstandard terminology such as "formation control," "cooperative navigation," or "multi-robot planning" without explicitly mentioning swarm intelligence. This limitation was partially mitigated through backward reference checking of the six included systematic reviews and forward citation tracking of highly cited primary studies.

2.3. Selection Criteria

Inclusion (IC) and exclusion (EC) criteria were established to delimit relevant articles and ensure the pertinence of the results.

The criteria considered are detailed in Table 1:

Table 1. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
IC1: Studies must present swarm algorithms applied specifically to UAV path planning. **IC2:** Must describe at least three operational characteristics of the algorithms, such as drone cooperation, dynamic task distribution, energy **IC3:** Must include quantitative evaluation metrics or comparisons with other state-of-the-art algorithms. **IC4:** Must be research articles, conference papers, or systematic reviews published in peer-reviewed academic sources. **IC5:** Must be written in English or Spanish.	**EC1:** Exclusive focus on individual UAVs without swarm coordination or multi-agent cooperation. **EC2:** Applications unrelated to path planning (e.g., solely flight control, stabilization, or communication systems with no impact on trajectories). **EC3:** Grey literature without peer review (technical reports, undergraduate theses, working papers). **EC4:** Insufficient methodological information or absence of quantitative results.

The exclusion of grey literature (EC3) warrants specific justification. Technical reports, undergraduate theses, and working papers were excluded to ensure that all analyzed studies had undergone peer review, thereby providing a minimum quality baseline for the evidence synthesized in this review. Although this criterion may omit relevant industry implementations of UAV swarm technology, the decision was made to prioritize methodological rigor and reproducibility over exhaustive coverage. This limitation is explicitly acknowledged in Section 4.

2.4. Quality Assessment

Given the heterogeneous nature of the included studies, which spanned simulation-based experiments, comparative benchmarks, and algorithm proposals with varying levels of validation, a formal quality appraisal was conducted to contextualize the strength of evidence underlying the review's conclusions. Rather than applying a standardized tool designed for clinical or experimental research, such as the Cochrane Risk of Bias tool, which would be poorly suited to the computational optimization literature, a domain-appropriate quality assessment framework was developed based on five criteria:

(Q1) Algorithmic description: Does the study provide sufficient detail to understand and potentially reproduce the proposed algorithm?

(Q2) Experimental design: Does the study define clear test scenarios with specified parameters, such as map dimensions, obstacle density, UAV count, and iteration limits?

(Q3) Baseline comparison: Does the study compare the proposed method against at least one established baseline algorithm?

(Q4) Statistical reporting: Does the study report results across multiple independent runs with measures of central tendency and variability, such as mean and standard deviation?

(Q5) Metric coverage: Does the study evaluate performance using at least three of the nine metrics identified in this review?

Each criterion was evaluated as met (1) or not met (0), yielding a quality score from 0 to 5. The assessment was performed independently by two authors, with the third author resolving discrepancies. Two studies initially classified as primary (IEEE7 and IEEE8) were reclassified as systematic reviews during this process, as they scored 1/5 due to the absence of novel algorithmic proposals or experimental validation. Following this reclassification, the final set of 25 primary studies yielded a mean quality score of 4.3/5 (SD = 0.9), with 24 studies (96.0%) scoring 3 or higher. The most frequently unmet criterion was Q4, statistical reporting with variability measures, which was met by 52.0% of studies, followed by Q5, coverage of at least three evaluation metrics, which was met by 80.0%. No studies were excluded based on quality scores.

Performance claims in this review, particularly regarding the 15–50% improvements attributed to hybrid methods, are reported as stated by the original authors within their specific experimental contexts. Therefore, they should not be interpreted as generalizable findings across standardized benchmarks, which do not yet exist in this field. The absence of such benchmarks is identified as a critical limitation in Section 4.

2.5. Study Selection Process

The initial search, conducted between November 15 and December 19, 2025, using the defined search strings, identified 2,761 records across the four academic databases. ScienceDirect contributed the largest share, with 1,404 records (50.9%), followed by Scopus with 771 (27.9%), IEEE Xplore with 314 (11.4%), and

ACM Digital Library with 272 (9.9%). After title and abstract screening, 51 articles were assessed for full-text eligibility, of which 20 were excluded based on the criteria detailed in Section 2.1. Figure 1 presents the PRISMA flow diagram for each phase of the selection process.

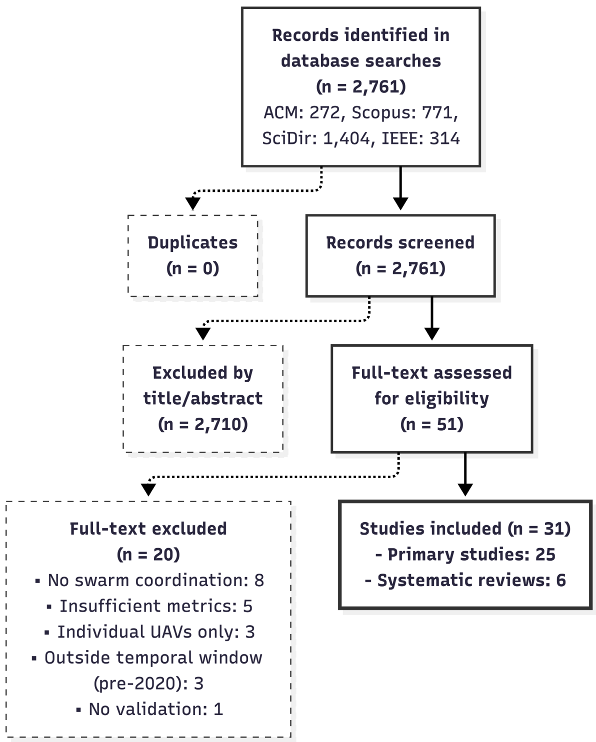

Figure 1. Flowchart of the selection process at each PRISMA phase.

The final sample comprised 25 primary studies and 6 systematic reviews. Only the primary studies were used for implementation counts, metric coverage, and comparative analysis. This distribution is shown in Table 2.

Table 2. Distribution of Articles by Source.

Source	Articles	Percentage	Year Range
Science Direct	7	22.60%	2020-2025
ACM Digital Library	6	19.40%	2021-2025
IEEE Xplore	9	29.00%	2020-2025
Scopus	9	29.00%	2021-2025
Total	**31**	**100%**	**2020-2025**

Each article was coded according to its source to facilitate traceability:

- SCI1–SCI7: ScienceDirect (7 articles)
- ACM1–ACM6: ACM Digital Library (6 articles)
- IEEE1–IEEE9: IEEE Xplore (9 articles)
- SCO1–SCO9: Scopus (9 articles)

Table 4 summarizes the 31 included articles by their ID, title, primary algorithm or study type, objective, and year of publication.

3. Results and Discussion

3.1. Data Extraction and Classification

The systematic analysis of the 25 primary studies enabled responses to the three research questions posed. Before presenting the findings, it is necessary to clarify an important methodological distinction between the two counting systems used in this analysis. Table 3 reports the total frequency of base algorithm appearances across all studies (n = 56), where a single study employing multiple algorithms, such as a hybrid combining PSO and ABC, contributes one count to each respective algorithm category. Table 3 presents the algorithmic building blocks of the field, while Table 5 summarizes the research contributions organized by methodological approach.

RQ1: Which algorithms are most commonly used in UAV path planning? The quantitative analysis reveals a clear dominance of three base algorithms in the UAV path-planning field. Table 4 summarizes the implementation frequency of the five most representative algorithm groups.

As the data indicate, PSO leads with 18 appearances (32.1%), followed by ACO with 11 (19.6%) and ABC with 8 (14.3%). GWO accounts for 7 appearances (12.5%), while other algorithms, such as GA, DE, and MPA, collectively contribute 12 additional cases (21.4%). Taken together, PSO, ACO, and ABC represent 66% of all identified algorithm appearances, consolidating their status as the fundamental reference algorithms in this domain. Figure 2 provides a visual representation of this distribution.

This predominance is not arbitrary: each algorithm has demonstrated specific strengths according to its operational context. PSO is widely used in defense scenarios requiring rapid convergence [33, 34]; ACO is prominent in search and rescue because of its route-optimization precision [35]; and ABC appears especially useful in agricultural settings, where energy efficiency is critical [36].

Table 3. Implementation Frequency of Base Algorithms

Algorithm	Implementations	Percentage
PSO	18	32.1 %
ACO	11	19.6 %
ABC	8	14.3 %
GWO	7	12.5 %
Others	12	21.4 %
Total	**56**	**100%**

Table 4. Complete Analysis of Included Articles Algorithms.

ID	Title	Primary Algorithm	Objetive	Year
SCI1	AUV path planning in a 3D marine environment	MCO (Multiple Swarm Co-Evolutionary)	Minimize distance, altitude, angle, currents	2024
SCI2	From PID to swarms: A decade of advancements	Systematic Review	Synthesize advances 2013–2023	2024
SCI3	Hybrid chaos game and grey wolf optimization	HCGO (GWO + CGO)	Minimize path length, threats, altitude	2025
SCI4	Large-scale UAV swarm path planning	PO-WMFDDPG	Maximize success rate and reward	2025
SCI5	MMPA: Modified marine predator algorithm	MMPA	Minimize multi-objective function	2024
SCI6	Novel task decomposed multi-agent TD3	TD-MATD3	Coordinate multiple UAVs	2024
SCI7	Path planning with online changing tasks	ORPFOA	3D routes for oil pipeline inspection	2020
ACM1	Enhanced Moth-Flame Optimization	EMFO	Optimize 3D path planning	2025
ACM2	Improved Particle Swarm Optimization Algorithms	DMSQPSO	Avoid premature convergence	2022
ACM3	AUV underwater 3D path planning based on particle swarm optimization	PSO-ASCS	Plan efficient underwater routes	2022
ACM4	Path Planning Methods for UAVs: Survey	Methods Review	Classify path planning techniques	2024
ACM5	UAV Path Planning with Improved PSO	PSO con Levy Flight	Avoid premature convergence	2024
ACM6	Swarm intelligence based robotic search in unknown maze-like environments	PSO + Bat Algorithm	Locate fixed target	2021
IEEE1	A Multigroups Cooperative Particle Swarm Algorithm	PSO multigroup	Improve accuracy in IoV	2024
IEEE2	A Survey on Swarm Intelligence Algorithms	SI Review	Classify SI techniques	2025
IEEE3	Artificial Hummingbird Algorithm	AHA	Optimize trajectories	2022
IEEE4	Distributed multi-UAV cooperation	NTVPSO-ADE	Distributed coordination	2022
IEEE5	Improved Bat Algorithm for UAV	IBA (BA + ABC)	Optimize 3D trajectories	2021
IEEE6	A Multi-UAV Formation Obstacle Avoidance Method	PSO	Maintain triangular formation	2025
IEEE7	Swarm Intelligence for UAV	SI Review	Analyze SI algorithms	2024
IEEE8	UAV Swarm Intelligence: Recent Advances	Multi-layer review	Synthesize SI architectures	2020
IEEE9	UCAV Path Planning Based on CPSO	CPSO	Minimize threats and fuel consumption	2020
SCO1	A Comparative Study of SI Algorithms	12 SI algorithms	Minimize combined cost	2021
SCO2	Multi-Strategy Enhanced MPA	MEMPA	Minimize multi-objective function	2025
SCO3	Bionic 3D Path Planning	Bionic-Krill	Minimize length, time, consumption	2024
SCO4	Intelligent Scheduling Technology	DQN-SISA	Minimize dynamic cost	2024
SCO5	Optimal path planning for drones	Improved ACO	Minimize distance and time	2022
SCO6	Path Planning via SI Algorithms	ABC vs PSO	Minimize total distance	2023
SCO7	Research on Unmanned Aerial Vehicle Path Planning	A* + BiLSTM	Minimize distance and time	2024
SCO8	Swarm intelligence: A survey of model classification and applications	Comprehensive review	Synthesize SI methods	2025
SCO9	UAV Path Planning Based on E-RRT	E-RRT	Minimize nodes and distance	2024

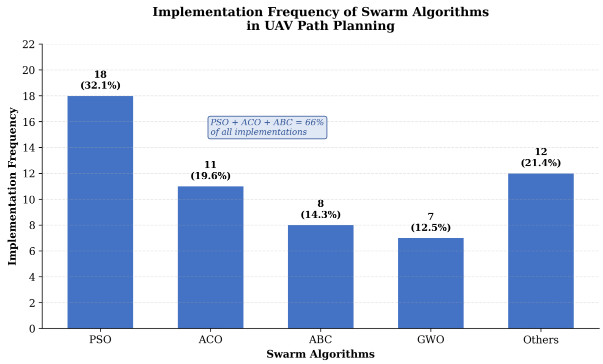

Figure 2. Implementation frequency of swarm algorithms in UAV path planning.

RQ2: How are swarm algorithms classified? The identified algorithms were organized into five taxonomic categories grounded in their theoretical foundations, optimization mechanisms, and coordination strategies. This classification was constructed bottom-up from the 25 primary studies and validated against the six systematic reviews that constitute the theoretical framework of the study. The categories are defined as follows: (1) Optimization Algorithms encompass classical metaheuristic methods that optimize objective functions through population-based search; (2) Hybrid Methods combine two or more distinct algorithmic approaches to overcome individual limitations; (3) Cooperative Control Algorithms specifically address multi-agent coordination through local behavioral rules; (4) Bio-inspired Algorithms simulate specific biological behaviors beyond classical swarm paradigms; and (5) AI-based Algorithms employ machine learning or deep learning for trajectory planning. These categories are mutually exclusive at the primary level; however, certain studies contribute to multiple categories when they present distinct methodological innovations, such as a cooperative control mechanism combined with a bio-inspired component. Table 5 presents the distribution.

Figure 3 complements the table by visualizing both the absolute count and the proportional weight of each category across the 36 classified implementations, making the structural hierarchy of the taxonomy immediately apparent.

Table 5. Distribution of Algorithms by Taxonomic Category.

Category	Count	Main Examples	Trend
Optimization Algorithms	13	PSO, ACO, GWO, ABC, DE, MPA	Stable
Hybrid Methods	10	MCO, HCGO, MMPA, PSO-ASCS, TD-MATD3	Growing
Cooperative Control Algorithms	6	Boids, UAV formations, multi-group coordination	Emerging
Bio-inspired Algorithms	4	AHA, Bat Algorithm, Bionic-Krill, EMFO	Emerging
AI-based Algorithms	3	PO-WMFDDPG, DQN-SISA, BiLSTM	Emerging

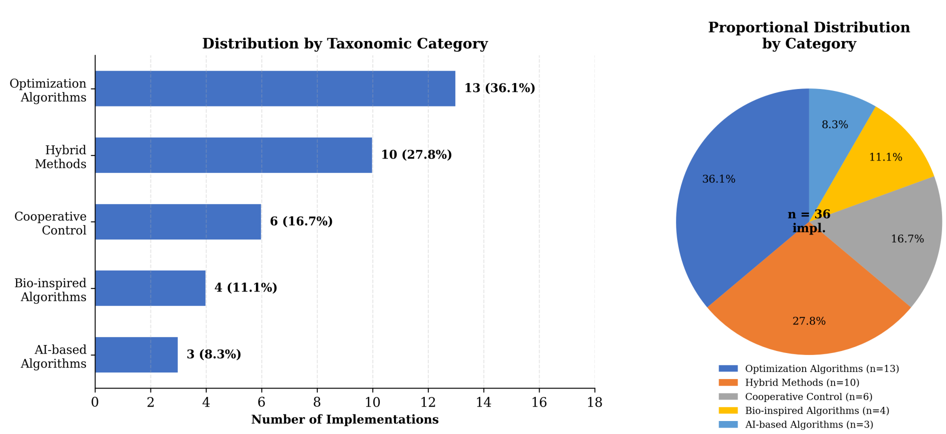

Figure 3. Distribution of swarm algorithm implementations by taxonomic category: absolute frequency (left) and proportional distribution (right).

The Optimization Algorithms category constitutes the foundation of the field, with 13 implementations of classical metaheuristic algorithms inspired by the collective animal behavior. Representative studies include ACM2 [37], ACM5 [38], IEEE1 [39], IEEE5 [40], IEEE6 [41], ACM6 [42], SCO6 [43], IEEE9 [34], SCO1 [44] ACM3 [45], and SCO5 [35].

Hybrid Methods emerge as the predominant research direction with 10 implementations, representing 27.8% of the total categories. These approaches strategically combine multiple techniques to overcome the inherent limitations of individual algorithms. For instance, MCO integrates AOA with SSA through co-evolution, HCGO combines GWO with CGO by incorporating chaotic variation, and TD-MATD3 fuses multi-agent reinforcement learning with task decomposition. This category includes SCI1 [46], SCI3 [33], SCI5 [47], SCI6 [48], ACM3 [45], IEEE5 [40], SCO2 [49], SCO3 [36], SCI7 [50], and SCO9 [51].

Cooperative Control Algorithms, identified in 6 studies, specifically address multi-UAV coordination through local behavioral rules. The distinguishing characteristic of these methods is decentralized coordination: they require no central controller and operate exclusively through local communication between neighboring agents. These implementations are documented in IEEE1 [39], ACM6 [42], IEEE4 [52], IEEE6 [41], SCI6 [48], and SCO6 [43].

Bio-inspired Algorithms comprise 4 implementations that simulate specific behaviors of natural organisms beyond classical swarm paradigms: AHA (Artificial Hummingbird Algorithm), Bionic-Krill, EMFO (Enhanced Moth-Flame Optimization), and IBA. These studies report path-quality gains ranging from 1.1% to 17.5% in their respective comparisons [36], [53, 54]. The corresponding studies are IEEE3 [53], IEEE5 [40], SCO3 [36], and ACM1 [54].

Finally, AI-based Algorithms represent the most promising technological frontier, with 3 implementations, equivalent to 8.3% of the total. PO-WMFDDPG employs Deep Reinforcement Learning with mean-field theory, achieving success rates above 90% in swarms of up to 120 UAVs and latency below 0.05 seconds [55]. DQN-SISA uses a Deep Q-Network for dynamic algorithm selection, yielding 8–15% reductions in operational costs [56]. A*+BiLSTM integrates classical planning with bidirectional neural networks for trajectory prediction [57]. These methods stand out for their capacity to adapt dynamically to changing environments through continuous learning.

The trend analysis reveals significant patterns: classical optimization algorithms maintain a stable presence as the backbone of the field, hybrid methods show accelerated growth, and the three emerging categories, cooperative control, bio-inspired, and AI-based, collectively account for 36.1% of all classified implementations, evidencing the active diversification of the field toward increasingly sophisticated approaches.

RQ3: What are the operational characteristics and their impact? The qualitative analysis of the 25 primary studies identified 12 fundamental operational characteristics that define the behavior of swarm algorithms. These characteristics were systematically extracted through thematic analysis of the reported implementations and subsequently contrasted with the taxonomies proposed in six prior systematic reviews of the field: SCI2 [26], covering 2013–2023; ACM4 [27], a methods survey; IEEE2 [28], an SI survey; IEEE7 [58], a UAV SI analysis; IEEE8 [59], a review of SI architectures; and SCO8 [29], a comprehensive review. These reviews provide consolidated conceptual frameworks for classifying and evaluating swarm algorithms in path planning.

The 12 characteristics were grouped by function into four dimensions: coordination, including cooperation through information exchange, dynamic task distribution in the event of failures, and local communication without centralized infrastructure; optimization, including global minimization of distance, time, and costs, exploration–exploitation balance, and advanced methods such as PSO, GA, and ACO; safety, including collision avoidance through minimum separation and real-time adaptation to obstacles; and efficiency, including scalability while maintaining performance, real-time operation, energy management.

Performance was reported using nine main metrics, summarized in Table 6.

Table 6. Coverage of Evaluation Metrics Across Studies.

Metric	Studies	Coverage
Path Length	24	96%
Convergence Time	22	88%
Robustness	20	80%
Computational Efficiencyl	19	76%
Success Rate	18	72%
Threat Exposures	16	64%
Energy Efficiency	14	56%
Trajectory Smoothness	14	56%
Area Coverage	12	48%

Path length dominates with 96% coverage, reflecting the priority given to spatial efficiency in path-planning research. It is followed by convergence time (88%) and robustness (80%), both of which are essential for real-time applications. Notably, metrics that are critical for real-world deployment, such as energy efficiency (56%) and area coverage (48%), receive comparatively less attention, revealing a persistent gap between academic research priorities and actual operational requirements.

The relative importance of characteristics and metrics varies according to the application domain. As detailed in Section 3.3, military missions and search and rescue operations account for the largest shares of studies (36.0% and 32.0%, respectively), followed by precision agriculture (20.0%) and infrastructure inspection (8.0%). Each domain imposes distinct metric priorities that reflect its specific operational demands. Figure 4 illustrates this distribution.

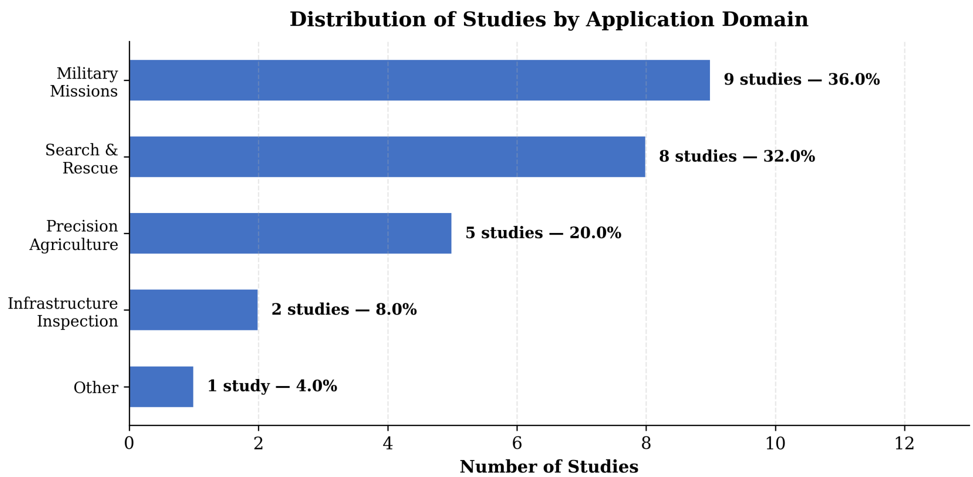

Figure 4. Distribution of studies by application domain.

3.2. Data Analysis

Comparative analysis was organized around convergence, solution quality, robustness, and computational complexity.

Because no standardized benchmarks exist, the reported figures must be interpreted as study-specific trends rather than direct head-to-head comparisons under identical conditions. Table 7 synthesizes the resulting performance profiles.

PSO generally converges faster than ACO and ABC, while hybrid methods tend to improve convergence, robustness, and adaptability in the reviewed experiments. ACO often favors solution quality, whereas AI-based methods provide the strongest dynamic adaptation in changing environments.

Table 7. Comparison of base versus hybrid algorithms.

Algorithm	Convergence	Quality	Robustness	Complexity
PSO	Medium	Alta	Medium	$O(n)$
ACO	Low	Very High	Alta	$O(n^2)$
ABC	Medium	Alta	Medium	$O(n)$
Híbridos	Very High	Very High	Very High	$O(n \log n)$

Computational complexity determines practical viability according to the operational context. PSO and ABC, with linear complexity O(n), are scalable for large-scale problems and real-time applications. ACO exhibits quadratic complexity $O(n^2)$ due to the iterative updating of the pheromone matrix, which limits its applicability in time-critical scenarios but justifies its use when solution quality is the priority. Hybrid methods, with O(nlogn) complexity, offer a balance between efficiency and performance.

Reported gains include path-length reductions of 1.1-17.5% and cost reductions of 10% to 13% in specific studies, while deep learning-based methods report inference times below 0.05 s [36], [49], [55].

A major limitation is the simulation-to-reality gap: none of the 25 primary studies validated results with physical UAV swarms. Most experiments involved 3 to 10 UAVs, with only one study testing scalability up to 120 units [55]. No systematic correlation between swarm size and path optimality could be established from the available data, as studies varied significantly in their experimental configurations, objective functions, and optimality criteria. Establishing such correlations would require standardized benchmarks that control for these confounding variables.

3.3. Analysis by Application Domain

The distribution of the analyzed studies by application domain reveals patterns of algorithmic specialization. As shown in Table 8, military missions account for 36.0% of studies, followed by search and rescue at 32.0%, agriculture at 20.0%, inspection at 8.0%, and other domains at 4.0%.

Table 8. Distribution of studies by application domain.

Domain	Studies	Percentage	Predominant Algorithms
Military missions	9	36.0 %	PSO, HCGO, CPSO
Search and rescue	8	32.0 %	ACO, PO-WMFDDPG
Agriculture	5	20.0 %	ABC, Bionic-Krill
Inspection	2	8.0 %	PSO-ASCS, Hybrid methods
Other (IoV)	1	4.0 %	Multi-group PSO
Total	**25**	**100%**	—

The military domain benefits particularly from PSO owing to its stability and rapid convergence, with variants such as HCGO [33] applied to threat minimization and CPSO [34] applied to fuel optimization. In search and rescue, ACO stands out for its precision in obstacle avoidance, while PO-WMFDDPG [55] achieves success rates above 90% while coordinating up to 120 UAVs. Agricultural applications favor ABC for its energy efficiency, complemented by Bionic-Krill [36], which achieves path-distance reductions of 1.1% to 17.5% relative to ACO and ABC. Inspection tasks favor hybrid methods such as PSO-ASCS [45] for their adaptability in variable environments.

It should be noted that the observed distribution may be influenced by publication bias, as military applications benefit from established funding streams and standardized problem formulations that facilitate academic publication, while civilian applications in logistics, environmental monitoring, and urban air mobility may be underrepresented due to proprietary constraints or the nascent state of regulatory frameworks. Additionally, the geographic distribution of research output was not analyzed in this review; regional preferences in research funding and journal accessibility may influence which algorithmic approaches receive greater attention in the indexed literature.

4. Conclusion

This review synthesized 31 studies published between 2020 and 2025, comprising 25 primary studies and 6 systematic reviews, to characterize swarm algorithms for UAV path planning following PRISMA guidelines. The evidence confirms the dominance of PSO, ACO, and ABC, which together account for 66% of the 56 identified algorithm appearances, while also showing that algorithm selection is strongly shaped by domain-specific demands.

The proposed five-category taxonomy indicates that classical optimization algorithms remain the backbone of the field, while hybrid methods constitute the main growth trend. Cooperative control, bio-inspired methods, and AI-based approaches suggest a shift toward more decentralized, adaptive, and learning-driven solutions. The nine-metric framework further shows that the literature prioritizes path length, convergence time, and robustness, while energy efficiency and area coverage remain comparatively underexplored.

Several limitations should be acknowledged. The reviewed studies are heterogeneous in scenario design, objectives, and reporting, which prevents strict meta-analysis and limits direct numerical comparison. In addition, all primary studies are simulation-based; therefore, issues such as latency, sensor noise, battery degradation, and aerodynamic interference remain insufficiently validated in real UAV swarms.

Future work should prioritize standardized benchmarks, stronger statistical reporting, public implementations, and physical validation with UAV swarms. Research opportunities are especially clear in AI-enhanced hybridization, extreme scalability, heterogeneous swarms, adversarial resilience, energy-aware replanning, and regulatory-compliant path planning. Overall, hybridization appears to be the most productive short-term direction, while artificial intelligence represents the most promising frontier for long-term scalability and autonomous adaptation.

Contributor role

- **Marcelo Rea-Guamán:** conceptualization, research, methodology, supervision, validation, writing – original draft and writing – reviewing and editing.
- **Andrea López-López:** conceptualization, formal analysis, research, methodology, supervision, validation and writing – reviewing and editing.
- **Andrés Almeida-Jara:** data curation, formal analysis, research, methodology, visualization and writing – reviewing and editing.

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