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Review

UAV Path Planning Trends from 2000 to 2024: A Bibliometric Analysis and Visualization

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Abstract: UAV path planning, as a key technology in the field of automatic control and intelligent systems, has demonstrated significant potential in various applications, including logistics and distribution, environmental monitoring, and emergency rescue. A comprehensive reassessment of the existing representative literature reveals that most reviews in this field focus on specific aspects and are largely confined to methodological investigations, primarily qualitative analyses that lack empirical data to support their conclusions. To address this gap, this study employs the mapping knowledge domain (MKD) method of bibliometrics, utilizing CiteSpace, VOSviewer, and Bibliometrix R package to analyze a total of 4416 documents from the Web of Science Core Collection (WOSCC) spanning from 2000 to 2024. Through retrospective analysis and scientific knowledge mapping, we first review the development of UAV path planning and categorize it into four distinct stages. Secondly, we identify key external features of the field. Using techniques such as co-citation analysis and keyword clustering, we then identify research trends, burst papers, and hotspots. Finally, we highlight five typical application scenarios of UAV path planning. The results of the study indicate that the field of UAV path planning has made significant advancements over the past two decades, particularly since 2018. These studies encompass various disciplinary areas, underscoring the increasing necessity for the integration of multidisciplinary approaches to UAV path planning in recent years. The aim of this study is to provide researchers with a comprehensive reference and new research perspectives while offering technical guidelines for professionals working in related applications.

Keywords: UAV; path planning; bibliometrics; co-citation analysis; visualization; CiteSpace

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1. Introduction

Unmanned aerial vehicles (UAV) were originally developed for military purposes and are recognized for their low cost, safety of operation, ease of operation, and high adaptability. Their origins trace back to the British "AT Plan" military experiments during World War I. Driven by artificial intelligence and automation, the application scope of UAVs has evolved from a singular military domain to a broad spectrum encompassing multi-application scenarios, multi-mission environments, and multi-technology integration. With the continued advancement of artificial intelligence and automation, UAV applications have steadily expanded, spanning from a narrow military focus to a diverse range of multi-application scenarios, mission environments, and technological integration. UAV technology has progressively evolved into a strategic industry, encompassing development, production, application, and training. It offers significant advantages in urban air mobility (UAM) [1], low-altitude logistics and distribution [2], communication relays [3,4], and agricultural plant protection [5].

UAV path planning research began in the 1960s. As a core challenge in UAV technology, path planning is a critical component of the UAV mission planning system. It is typically defined as an optimization problem constrained by factors such as terrain, threat distribution, UAV maneuvering capabilities, endurance, and range. By solving the objective function, the goal is to find an optimal or suboptimal path from the starting point to the target, ensuring safety, efficiency, and low fuel use [6]. Depending on the number of UAVs, UAV path planning is classified into single-UAV path planning and multi-UAV path planning. Multi-UAV cooperative path planning is based on single-UAV path planning, requiring consideration of inter-UAV collisions and cooperation. It introduces concepts such as formation obstacle avoidance, formation maintenance, and temporal coordination to ensure the synchronization of multi-UAVs in spatial, temporal, and task dimensions, thereby optimizing overall performance.

Currently, academic reviews of UAV path planning often categorize path planning algorithms into traditional, intelligent, and hybrid (fusion) algorithms. However, this broad classification tends to overlook the specific demands and challenges of different application domains. In response, scholars have increasingly provided more nuanced discussions from various perspectives. For instance, Shiller Z [7] classified path planning algorithms based on the degree of environmental information awareness, distinguishing between offline and online path planning methods. Debnath et al. [8] categorized these algorithms into global and local path planning approaches in single UAVs, as well as multi-UAV path-planning methods evaluating them in terms of adaptability, limitations, and effectiveness in obstacle avoidance. Castro et al. [9] further refined UAV cluster path planning techniques, dividing them into four categories based on technological domains: reinforcement learning techniques, evolutive computing techniques, swarm intelligence techniques, and graph neural networks. Aggarwal et al. [10] adopted a different criterion, classifying UAV path planning techniques into representative, collaborative, and non-collaborative techniques, with a focus on network coverage and connectivity. Abdulsaheb et al. [11] differentiated between static and dynamic path planning based on environmental changes. Yu et al. [12] proposed a classification of path optimization methods, categorizing them into minimum trajectory optimization, hard constraint optimization, and soft constraint optimization. Yang et al. [13] offered a comprehensive classification, dividing path planning methods into five major categories—sampling-based algorithms, node-based algorithms, mathematical model-based algorithms, bio-inspired algorithms, and multi-fusion-based algorithms—based on their working principles and time complexity. These categorizations provide valuable insights for UAV path planning research, offering better strategies for addressing practical challenges in diverse application areas.

This paper integrates the mapping knowledge domain (MKD) method of bibliometrics with the WOSCC as the data source. We employ CiteSpace, VOSviewer, and the Bibliometrix R package for visualization and analysis, presenting the findings in graphical form. The study aims to provide both quantitative and qualitative analyses of the evolution and emerging trends in this field, offering researchers comprehensive references and new perspectives for future research.

The main contributions of this paper are as follows:

1. We examine the progression of UAV path planning from multiple perspectives and delineate four distinct stages in its evolution.
2. We offer a comprehensive analysis of advancements in UAV path planning through a bibliometric perspective. This analysis highlights the key contributors in this field, including academic journals, research institutions, and geographical regions, while also outlining the relevant academic disciplines involved.
3. We examine the research hotspots and trends in the field of UAV path planning from 2001 to 2024, while also highlighting recent research findings in application scenarios since 2022.

This paper is structured as follows:

Section 2 provides an overview of the evolution of UAV path planning and its associated models, categorizing the development into four distinct stages and presenting a foundational model. Section 3 outlines the research design, detailing the data sources, visualization tools, and methodology employed in this study. Section 4 analyzes the external characteristics of the publications, including the volume of publications, contributing journals, affiliated institutions, country/region, and subject areas. In Section 5, a co-citation cluster analysis is conducted to identify and summarize four key research trends in UAV path planning, followed by an examination of emerging literature in the field. Section 6 employs keyword clustering to identify current research hotspots and explores application scenarios for UAV path planning. Finally, Section 7 provides a summary of the key research findings.

2. Evolution, Methods, and Models for UAV Path Planning

2.1. Stages of UAV Path Planning Development

Based on the evolution of UAV path planning, we classify the research into four distinct stages, organized both chronologically and by key technological advancements:

- Early Exploratory Stage

The study of UAV path planning began in the mid-20th century, initially focusing on military applications. At this stage, UAV control systems were in the early stages of development, characterized by high research and development costs and limited manufacturing capabilities. These early UAVs lacked autonomous decision-making abilities and were primarily used as combat security platforms. They required pre-programmed, fixed procedures to perform a variety of military tasks [14]. The early path planning algorithms were primarily concerned with obstacle avoidance in known, static environments. During this period, the first task allocation methods, such as those based on linear programming [15] and integer programming [16], emerged. These methods were closely linked to military operations research and were applied to solve path-related challenges in combat-focused scenarios. Typical applications included communication relay, target training, electronic countermeasures, reconnaissance and surveillance, military strikes, and logistical support [17,18].

- Classical Algorithm Stage

During the first wave of development of artificial intelligence in the 1950s–1970s, its emergence led to the introduction of several basic theories, such as heuristic search methods and logic-based reasoning methods. This period saw the diversification of path planning algorithms, with the development of graph search-based methods, such as depth-first search (DFS) [19] and breadth-first search (BFS) [20]. In 1959, Dutch computer scientist Edsger W. Dijkstra introduced Dijkstra's algorithm [21], which computes the shortest path from a starting point to all vertices in a graph by iteratively traversing all nodes and updating the distances to neighboring nodes. Unlike traditional graph search methods, Dijkstra's algorithm incorporates a minimum weight selection mechanism, which prioritizes the known shortest paths using a greedy strategy. This significantly reduces the search space and proves advantageous when dealing with large graphs, particularly in weighted graphs. In 1968, Peter Hart et al. proposed the A* algorithm [22], an enhancement of Dijkstra's algorithm that incorporates a heuristic function h(u). This heuristic function guides the search process towards the target, minimizing unnecessary exploration and thereby improving search efficiency [23]. Building upon these advancements, subsequent algorithms such as iterative deepening A* (IDA*) [24] and lifelong planning A* (LPA*) [25] were introduced. These algorithms, which integrate concepts from artificial intelligence and incremental updates, are better suited for solving path planning problems in dynamic environments.

Traditional graph search-based algorithms, while effective in many applications at that time, often exhibit limitations when applied to complex environments. In particular, in dynamic, high-dimensional, and unstructured environments, these algorithms may require substantial computational resources and struggle to adapt to real-time changes. To address these challenges, model-based or physics-based path planning algorithms, such as the artificial potential field (APF) method [26], emerged as a local path planning method. Unlike global search algorithms, APF employs a feedback control strategy that simulates the attractive force exerted by the target point on the UAV and the repulsive forces from obstacles. The UAV then moves according to the resultant force. The APF method offers several advantages, including real-time responsiveness, high operational efficiency, and low computational demands.

However, the basic APF method only considers fixed distances between the UAV, target point, and obstacles. In the presence of dynamic obstacles or moving target points, its real-time performance may deteriorate. Moreover, the path generated by the force field calculation is often linear, potentially resulting in sharp turns or abrupt changes in direction. This can prevent the algorithm from finding a globally optimal solution in complex environments. To overcome these limitations, sampling-based path planning methods, such as probabilistic roadmap (PRM) [27] and rapidly exploring random tree (RRT) [28], were introduced. These algorithms explore the state space by constructing a random tree, independent of the environment's geometric model. By utilizing random samples, they achieve probabilistic completeness instead of requiring a complete model of the environment. This approach not only helps to manage high-dimensional spaces but also enables the algorithms to effectively adapt to dynamic obstacles and overcome the "curse of dimensionality". In the context of UAV path planning, numerous variants of the RRT algorithm have been developed to enhance convergence speed towards the optimal solution [29,30]. As computational power has increased, further improvements to traditional classical algorithms have focused on balancing path smoothing, computational efficiency, and real-time performance, particularly in terms of improving global optimality and local adaptability. In summary, the algorithms introduced during this stage laid the foundational groundwork for the subsequent advancements in path planning research.

- Intelligent Algorithm Application Stage

In the 1990s, with the rise of biomimetic approach and increasing influence of artificial intelligence research, there was a shift towards structural simulation approaches. This era saw a focus on modeling human biological neural networks, which led to the development of swarm intelligence algorithms inspired by biological systems. These algorithms, such as the ant colony optimization (ACO) [31], particle swarm optimization (PSO) [32], bacterial foraging algorithm (BFA) [33], and bee colony optimization (BCO) [34], gained widespread application.

Swarm intelligence (SI) refers to the phenomenon in which multiple simple agents exhibit complex intelligent behaviors through cooperation, guided by simple local rules and interactions, to solve intricate problems. As the study of SI advanced, its conceptual scope broadened. For instance, Wang et al. [35] classified SI into two broad categories: bio-inspired swarm intelligence and human-machine hybrid swarm intelligence. Furthermore, bio-inspired swarm intelligence was subdivided into Single-population swarm intelligence, isomorphic multi-population swarm intelligence, and heterogeneous multi-population swarm intelligence. Xiao et al. [36] outlined four developmental stages of SI and discussed various types of cooperative behaviors in swarm intelligence systems, including indirect regulatory cooperation in lower organisms, direct communicative cooperation in higher organisms, and shared intention-based collaboration in humans.

Swarm intelligence algorithms are heuristic search techniques inspired by the collective behavior of natural populations. Its design concept is straightforward. These algorithms are inspired by the observation of animal behaviors. By analyzing the natural behaviors of animals, such as fish schooling, the ambush tactics of felines, and the following behavior of snakes, we gain insights into how animals efficiently address challenges in their environment, such as finding food, evading predators, or locating mates. The subsequent step involves feature extraction, wherein key characteristics are identified from these behaviors, including social structures, communication methods, and decision-making mechanisms. For example, the swarming behavior of fish may involve close collaboration and information sharing, while the ambushing behavior of felines may rely on stealth and surprise tactics. These features are then utilized to design algorithms that mimic animal behaviors to solve engineering problems, such as the artificial fish swarm algorithm (AFSA), owl migration algorithm (OMA), cat swarm optimization (CSO), and snake optimization algorithm (SOA). After the design phase, a pilot test is conducted to assess the algorithms' performance in a controlled environment, verifying their effectiveness, identifying potential limitations, and providing insights for further optimization. Finally, the validated algorithms are applied to real-world engineering problems, including areas such as engineering problems (Eng. Prob), machine learning (ML), computer vision (CV), and economic and management (E&M).

These algorithms aim to find optimal solutions by simulating the distributed computations, information transfer, and collaborative mechanisms observed in nature. This results in the formation of a self-organized structure capable of solving complex problems through local interactions and collective cooperation [37,38]. As of today, swarm intelligence remains a vibrant area of research, with scholars continuously developing new variants and hybrid algorithms by integrating swarm intelligence with other optimization techniques. These advancements provide fast and reliable methods for solving complex optimization problems in a variety of fields. Applications of swarm intelligence include, but are not limited to, high-precision mapping [39], sensor fusion, dynamic environment adaptation [40], transportation logistics [41], network routing [42], robotic scheduling [43], power system optimization [44], fault diagnosis [45], data mining [46], layout optimization [47], and signal processing [48].

- Multi-Intelligence Collaborative Stage

With the emergence of large-scale pre-trained models (LLMs) [49] and heterogeneous multi-agent systems (MASs) [50,51] in the field of embodied intelligence (EI), multi-agent path finding (MAPF) algorithms have become more important. MAPF introduces the concept of intelligent body conflict resolution within the framework of intelligent algorithms [52]. The key challenge in MAPF is ensuring that multiple intelligences travel along pre-planned paths simultaneously without conflict, meaning they must avoid situations where two or more agents occupy the same spatial position at the same time. This concept is particularly useful in solving the multi-UAV target assignment and path planning problem (MUTAPP) [53]. Compared to single-UAV path planning, MUTAPP requires consideration of inter-UAV collision avoidance and coordination, which includes maintaining formation and avoiding obstacles. The aim is to achieve coordination across multiple UAVs in spatial, temporal, and task dimensions.

MAPF algorithms can be classified into centralized and distributed planning methods [54], and further into optimal and suboptimal algorithms based on the effectiveness of the path planning [55]. Common types of conflicts encountered in MAPF include edge conflicts, vertex conflicts, follow conflicts, and cyclic conflicts. Vertex conflict occurs when two agents occupy the same vertex simultaneously. Edge conflict involves scenarios such as agents swapping positions or one agent overtaking another. Follow conflict refers to the situation where a conflict may arise in path planning when one agent attempts to follow another agent and cyclic conflict refers to a conflict that occurs when multiple agents form a cyclic dependency in path planning. To resolve conflicts, the affected node is split, creating new successor nodes, and additional constraints are introduced to prevent further conflicts. MAPF algorithms typically combine global path planning with local obstacle avoidance strategies. Several methods have been developed to detect and resolve conflicts, including conflict-based search (CBS) [56], the branch-and-cut-and-price (BCP) algorithm [57], distributed task allocation algorithms such as the contract net protocol [58], heuristic guided conflict-based search (HG-CBS) algorithm [59] and multi-agent algorithms applied to robotics [60]. These algorithms share a common goal of dynamically allocating computational resources, prioritizing overall system efficiency, and achieving multi-objective optimization. Taking HG-CBS as an example, which utilizes two heuristic functions including path cost and number of basic conflicts, which, respectively, represent the cost from the current to the goal state and the level of conflict in the current state. HG-CBS algorithm features a two-layer architecture, consisting of a decision layer and execution layer, which works iteratively to generate conflict-free trajectories for all agents. The decision layer searches the constraint tree to detect conflicts and introduces relevant constraints, and the constraint tree encodes path constraints, with each node representing a specific constraint. The execution layer determines optimal paths under the given constraints using an optimized search strategy, such as A*, and incorporates heuristic functions to improve search efficiency. The HG-CBS algorithm supports various heuristic combinations, enabling the selection of the most suitable strategy for specific scenarios. Its flexible framework allows easy adaptation to other multi-agent path planning problems.

Worth mentioning, computational intelligence (CI) has become widely applied, with learning-based methods showing promising results in UAV path planning [61]. Reinforcement learning (RL), in particular, does not require a precise model of the environment's dynamics, allowing it to learn optimal policies through trial-and-error. This makes RL highly adaptable, with strong generalization capabilities that can extend to environments involving large-scale intelligence. In the context of path planning, multi-agent reinforcement learning (MARL) algorithms have demonstrated great potential in solving MAPFs within dynamic and changing environments, exhibiting strong capabilities in solving MUTAPPs. Recently, a variety of MARL algorithms have been proposed, such as centralized learning with distributed execution [62], multi-agent deep deterministic policy gradient (MADDPG) [63], and independent Q-learning (IQL) [64–66].

Solving MAPF problems using RL methods presents several challenges, including sparse environmental rewards and complex dynamics, which can lead to slow learning and poor learning outcomes when directly applied to MAPF problems. To address these issues, researchers have employed various combinatorial techniques to enhance RL-based MAPF approaches, enabling them to scale effectively to environments with thousands of agents. These improvements significantly enhance both the quality and efficiency of solutions. Based on the nature of these improvements, they can be broadly categorized into three types: expert demonstration-based methods, improved communication-based methods, and task decomposition-based methods.

Expert demonstration methods primarily involve combining RL with imitation learning (IL), such as pathfinding via reinforcement and imitation multi-agent learning (PRIMAL) [67]. These methods aim to leverage expert demonstrations to guide the learning process. Improved communication-based methods address the challenge of enabling multiple agents to communicate and coordinate effectively in environments where the agents' interactions are largely unknown. Task decomposition-based methods, such as the hybrid policy (HPL) approach [68], break down the MAPF problem into two primary subtasks: reaching the goal and avoiding conflicts. These methods utilize RL techniques, such as deep Monte Carlo tree search (DMCTS) [69] and the Q-hybrid network approach [70], to map agent observations to actions and integrate strategies for both goal reaching and conflict avoidance. This hybrid approach enables each agent to exhibit two types of behavior: individual behaviors (for goal achievement) and cooperative behaviors (for conflict avoidance). The resulting hybrid strategy outperforms traditional single-agent RL methods in terms of overall effectiveness.

For ease of presentation, we provide an abstraction of the key ideas and methods across the four stages of UAV path planning, as illustrated in Figure 1.

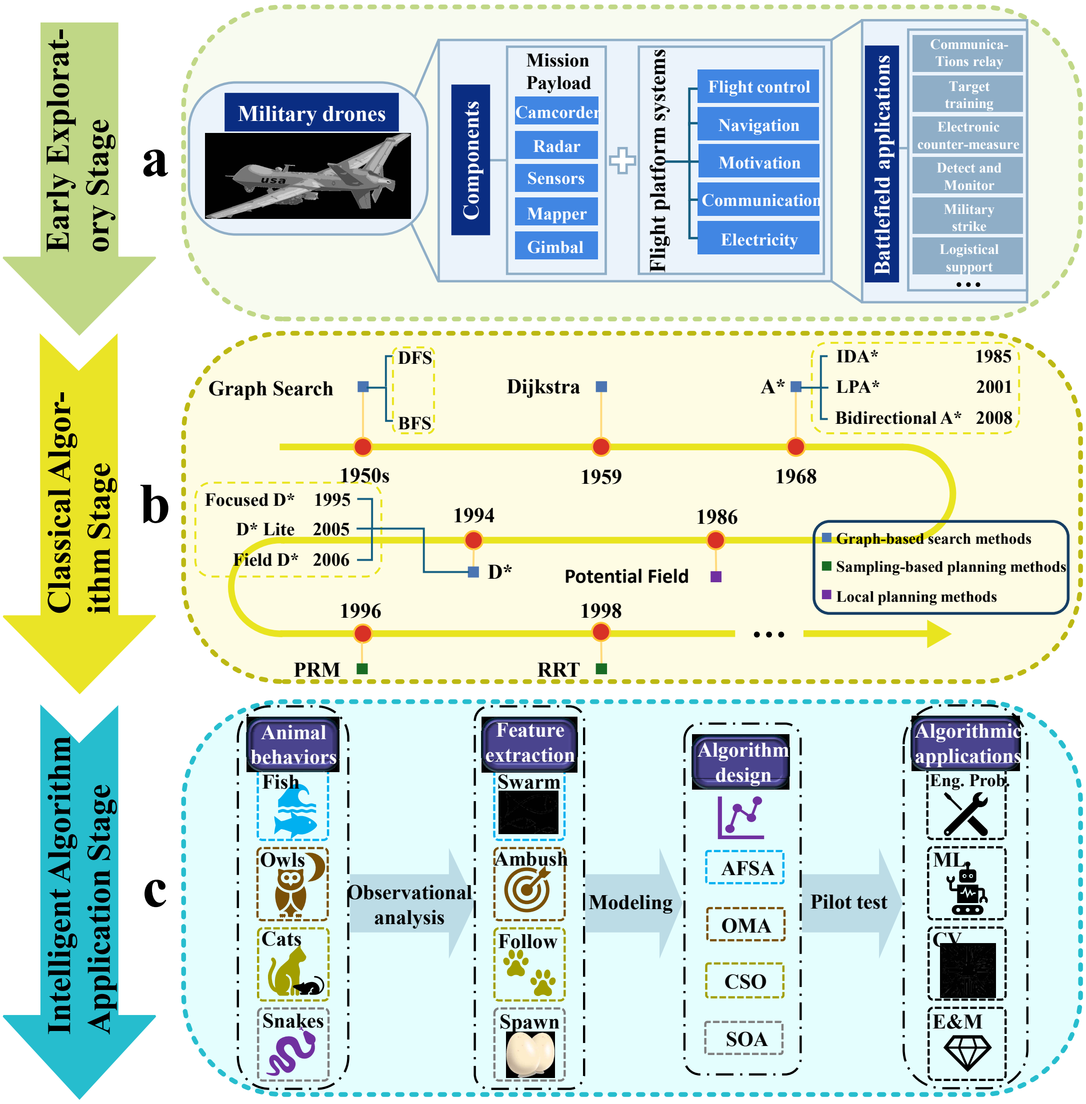


Figure 1. *Cont.*

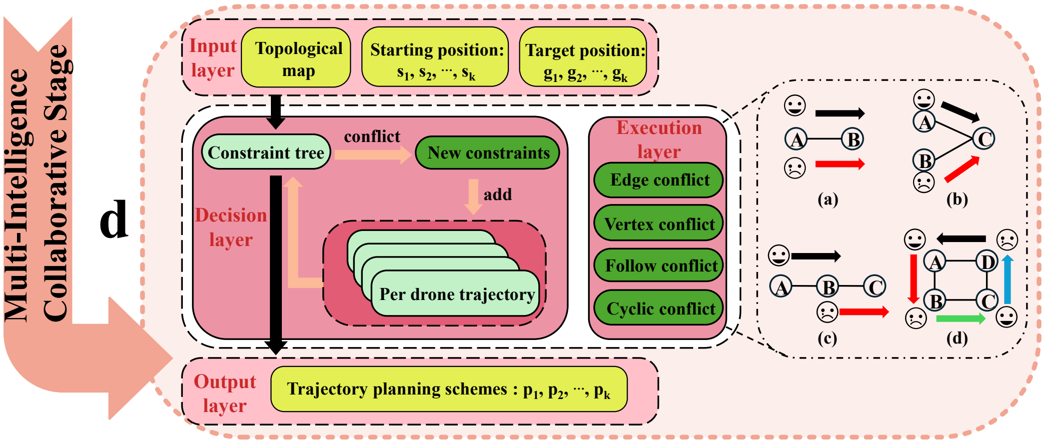


Figure 1. Diagram of the four stages of UAV path planning development. Note: The arrows on the left indicate the names of the four stages, while the four frame diagrams on the right, labeled **a**, **b**, **c**, and **d**, represent the following, in order from top to bottom: (**a**) the introductory diagram of the military UAVs in the early exploratory stage, (**b**) the timeline diagram of the classical algorithm stage, (**c**) the flowchart of the design of the swarm intelligence algorithms, and (**d**) the flowchart depicting the principle of heuristic guided conflict-based search (HG-CBS).

2.2. Basic Model

To address the UAV path planning problem, it is common to formulate it as a state-space route optimization problem. Optimization algorithms are subsequently used for real-time dynamic path planning to determine the optimal solution. This approach must consider aerodynamic constraints, the UAV's intrinsic performance limitations, and environmental factors. A combination of accurate environmental data, constraints, and high-performance path planning algorithms is essential for achieving more optimal path planning outcomes.

In this paper, the UAV's steering angle, climb angle, minimum turning radius, flight altitude, and endurance time are used as constraints. Additionally, a cost function is introduced to evaluate the relative advantages and disadvantages of different paths [10]. The basic model for path planning is constructed as follows:

Given a starting time t_s and initial position $\delta(0) = P_s$, a target time T and target position $\delta(T) = P_t$, the condition of existence is: $\phi = \delta(\beta) \in W_{free}$, for $\beta \in [0, T]$, ϕ was defined the path planning for UAVs. The optimal path planning can be expressed as $\delta\prime(c, t, e) = \min\delta(c, t, e)$, where δ is a function of the set of feasible paths and $\delta\prime$ is a function representing the computation of the optimal path.

Let (x_i, y_i, z_i) represent the current position of the UAV, $(x_{i+1}, y_{i+1}, z_{i+1})$ the next node position, and $(x_{i-1}, y_{i-1}, z_{i-1})$ the previous node position.

The symbols are defined as shown in Table 1:

Table 1. Definition of symbols.

Symbol	Definition	Symbol	Definition
W_{free}	Free space available for drone flight	$\delta(t)$	Position function of the drone at time t
P_s	The initial position of the drone	v	Flight speed of the drone
P_t	The target position of the drone	α	Motor speed multiplier
$P_{\min}$	Minimum power required for drone startup	l	Number of communication links on the path of the drone
$P_{\max}$	Maximum power of the drone	t_i	Time taken between flight nodes of the drone

Table 1. *Cont.*

Symbol	Definition	Symbol	Definition
T	Total flight time of the drone	t_s	Startup time of the drone
E	Energy consumption cost	t_o	Overhead time
H	Altitude cost	t_h	Time spent hovering by the drone
C	Length cost	h_{ref}	Flight reference altitude of the drone
T_{com}	Communication cost	d_{ij}	Distance from point i to point j
W	Threat cost	d_i	Distance from the drone to the nearest obstacle
P	Smoothing cost	φ_i	The current horizontal yaw angle of the drone
M	Total flight cost	θ_i	The current vertical climb angle of the drone
$n_{y\max}$	Maximum normal load factor of the drone	r_i	The current turning radius of the drone

Constraints (1)–(5) are defined as follows:

$$0 \le \arccos\left[\frac{(x_i - x_{i-1})(x_{i+1} - x_i) + (y_i - y_{i-1})(y_{i+1} - y_i)}{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}\sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}}\right] \le \varphi_{\max} \quad (1)$$

$$0 \le \theta_i = \frac{|z_i - z_{i-1}|}{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}} \le \tan\theta_{\max} \quad (2)$$

$$r_i \ge r_{\min} = \frac{(v_{\min})^2}{g\sqrt{(n_{y\max})^2}} \quad (3)$$

$$H_{\min} \le h_i \le H_{\max} \quad (4)$$

$$\sum_{i=1}^{n} t_i < t_{\max} \quad (5)$$

- Equation (1) represents the UAV steering angle constraint, where $\varphi_{\max}$ denotes the maximum steering angle of the UAV. If the steering angle is excessively large, the UAV may lose control or incur damage. It is crucial to ensure that the steering error does not exceed the mechanical and control system's limitations.
- Equation (2) represents the UAV climbing angle constraint, where $\theta_{\max}$ denotes the maximum climbing angle. This constraint limits the vertical climb or descent to prevent loss of control due to excessively steep flight paths.
- Equation (3) represents the UAV turning radius constraint, where $r_{\min}$ denotes the minimum turning radius and $v_{\min}$ represents the minimum flight speed. These constraints prevent the UAV from losing control due to excessively small turning radii.
- Equations (4) and (5) represent the flight altitude and endurance constraints, respectively. $H_{\max}$ and $H_{\min}$ denote the maximum and minimum flight altitudes within the flight environment. $\sum_{i=1}^{n} t_i$ denotes the total flight time for the UAV to reach its current position, and $t_{\max}$ represents the maximum endurance time.

Equations (6)–(12) define the various cost components used in the path planning model. These costs are critical in evaluating the overall efficiency and safety of the UAV's flight path.

$$E = (P_{\min} + \alpha h)t + P_{\max}(\frac{h}{v}) \quad (6)$$

$$T_{com} = t_s + (t_o + t_h)l \quad (7)$$

$$C = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2} \quad (8)$$

$$W = \sum_{i=1}^{n} \frac{1}{d_i^2} \tag{9}$$

$$H = \sum_{i=1}^{n} \left(h_i - h_{ref}\right)^2 \tag{10}$$

$$P = \sum_{i=1}^{n-1} \left[\left(\varphi_{i+1} - \varphi_i\right)^2 + \left(\theta_{i+1} - \theta_i\right)^2 \right] \tag{11}$$

$$M = E + T_{com} + C + W + H + P \tag{12}$$

- Equation (6) represents the energy cost, which incorporates the minimum power $P_{\min}$, altitude h, maximum power $P_{\max}$, and speed v, reflecting variations in the UAV's energy consumption under different flight conditions.
- Equation (7) represents the total communication cost, which depends on the number of communication links l between the UAV and the control station, as well as the communication time. The value of l is correlated with the distance between the UAV and the control station. Equation (8) represents the range length cost, which is calculated based on the total length of the UAV's flight path.
- Equation (9) represents the threat cost, which depends on the distance d_i between the UAV and the threat.
- Equations (10) and (11) represent the altitude cost and smoothing cost, respectively, both of which are related to the UAV's energy consumption and flight stability. Equation (12) represents the total cost of the flight, providing a comprehensive metric to assess both the efficiency and safety of the UAV's flight path.

By optimizing the total flight cost, the theoretically optimal flight path can be determined. In different environments, variable weights can be applied to different cost components to prioritize specific aspects and achieve path optimization. For instance, in urban environments where obstacle avoidance is critical, the threat cost can be assigned to a higher weight. In contrast, in open areas where energy efficiency is more important, the energy cost can be prioritized.

3. Study Design

3.1. Data Sources

Data for this study were extracted from the WOSCC, which is regarded as the world's leading multidisciplinary academic literature abstract indexing database. WOSCC provides comprehensive global scientific research information and is considered the most informative database for bibliometric analysis, consisting of several indexes: the Science Citation Index Expanded (SCI-E), the Social Science Citation Index (SSCI), the Arts & Humanities Citation Index (A&HCI), the Conference Proceedings Citation Index-Science (CPCI-S), the Conference Proceedings Citation Index-Social Science & Humanities (CPCI-SSH), and the Emerging Sources Citation Index (ESCI) [71].

For the literature search in WOSCC, the selected document types included "articles", "reviews", "editorials", and "proceedings papers". The search range was 1 January 2000–1 November 2024. The primary search keywords were "UAV", and "Path Planning". Recognizing that the keywords "UAV" and "Path Planning" appear in various forms across academic literature, we broadened the search by consulting Thesaurus.com and Synonym.com. The supplementary search terms were derived as follows:

TS = ("UAV" OR "Drone" OR "Unmanned Aerial Vehicle" OR "Unmanned Aircraft" OR "Unmanned Combat Aerial Vehicle" OR "Quadcopter" OR "Hexacopter" OR "Octocopter" OR "Fixed-Wing UAV" OR "Aerial Vehicle") AND TS = ("Trajectory Planning" OR "Route Planning" OR "Path Planning" OR "Trajectory Optimization" OR "Route Optimization" OR "Path Optimization")

The dataset was downloaded from WOSCC in tag-delimited plain text files, yielding a total of 5780 documents. To ensure data rigor, documents with abnormal or low relevance were manually excluded using Excel. Terms such as "driverless vehicle" and "autonomous vehicle" were searched to filter out irrelevant papers. Additionally, documents not focused on UAVs as the primary research subject, as well as retracted and duplicate papers, were excluded. After this process, a final dataset of 4416 relevant publications was identified.

3.2. Visualization Tools

In this study, we primarily utilized three visualization tools—CiteSpace (version 6.4.1), VOSviewer (version 1.6.20), and the Bibliometrix R package—to analyze the literature. These tools are briefly described as follows:

CiteSpace is a professional academic data analysis and visualization software, developed by Dr. Chaomei Chen of Drexel University and the WISE lab of the Dalian University of Technology [72,73]. Relying on Java programming, CiteSpace applies mathematical and statistical algorithms to explore the interactions within the literature metadata and generates visualizations in the form of knowledge graphs. It is commonly used for analyzing co-words, constructing co-citation networks, and predicting frontier research directions.

VOSviewer is an open-source, Java-based tool for scientific knowledge mapping, co-developed by Nees Jan van Eck and Ludo Waltman at Leiden University, the Netherlands [74,75]. It offers powerful text-mining functionalities and is typically used to visualize co-citation networks, coupling networks, and clustering analyses in the scientific literature.

Bibliometrix is an R-based online analysis software package [76], designed for quick and efficient processing of plain text data to automatically generate various bibliometric indicators. It is primarily employed to analyze papers' external characteristics.

3.3. Methodology

We present the main methodology used in this paper—bibliometrics. Bibliometrics is a field of study focused on the quantitative analysis of literature, citations, and other bibliographic data to derive insights into research trends and performance [77]. This approach mitigates, to some extent, the limitations of subjective inductive reviews, and enhances the objectivity and reliability of analysis. Bibliometric indicators are essential in evaluating both the productivity and quality of research outputs. These indicators can be categorized into three types: quantitative, qualitative, and structural, each providing valuable information about the impact and interconnections among literature, authors, and research areas [78]. In recent years, bibliometric analysis has become an important tool for monitoring scientific advancements, assessing research performance, and identifying future research opportunities.

This paper presents an analysis of the literature related to UAV path planning from a bibliometric perspective, and the following describes the parameters involved in CiteSpace and VOSviewer, the main tools used in this paper.

CiteSpace models the knowledge structure of a specific domain through a synthetic network derived from the time series of literature based on bibliographic records [72]. Time slicing techniques are employed to construct an overview network of relevant literature, synthesized from individual network models over time. In a CiteSpace-generated network, nodes represent items in the dataset, and links between pairs of nodes indicate co-occurrence relationships. The importance of a concept or cited reference is indicated by the size of the node, displayed as a citation tree ring. Different colors denote the time when the link first appears. Key metrics, including temporal metrics (such as citation bursts) and structural metrics (such as median centrality, modularity, and profile scores), are referred to as sigma metrics [79]. These sigma metrics combine both structural and temporal attributes of nodes, including median centrality (BC) and citation bursts [80]. Modularity (Q-score, ranges from 0 to +1) measures the quality of network clustering, while the within-cluster similarity (WMS, S-score, ranges from −1 to +1) evaluates the quality of cluster configuration [81,82]. Typically, when Q-score > 0.3, the network structure can be considered significant. Furthermore, the closer the value of S-score is to 1, the higher the homogeneity of the network, making the clustering configuration more reasonable.

For the analysis in this paper, the parameters for CiteSpace are set as follows: the time range was January 2000–November 2024, with a time slice of one year. The node types selected are country, category, reference, and keyword. The value of k is set to 25, and the CiteSpace log-likelihood ratio (LLR) clustering method is applied. The links parameter uses the cosine algorithm to measure the strength of associations between network nodes, where c_{ij} represents the co-occurrence frequency between nodes i and j, additionally, s_i and s_j denote the individual frequencies of i and j [83], as shown in Equation (13).

$$Consine(c_{ij}, s_i, s_j) = \frac{c_{ij}}{\sqrt{s_i s_j}} \tag{13}$$

The user parameters for VOSviewer are relatively straightforward to configure. Data objects are divided by constructing a correlation matrix for all variables to calculate similarity values. The limit parameter variables are then adjusted, and clusters with high consistency and stability are generated [84]. The optimal clustering result is achieved when Q-score is maximized, the related principles can be described by Equations (14)–(16).

$$Q = \frac{1}{2m}\sum\nolimits_{i<j} \delta(x_i, x_j) w_{ij} \left(c_{ij} - \gamma \frac{c_i c_j}{2m} \right) \tag{14}$$

$$M = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{bmatrix} \tag{15}$$

$$w_{ij} = \frac{2m}{c_i c_j} \tag{16}$$

In the equations, m represents the total number of connections in the network, c_{ij} denotes the number of connections between nodes i and j, while c_i and c_j represent the total number of connections for nodes i and j, respectively. x_i indicates the cluster to which a node belongs, w_{ij} denotes the weight value of the connection, and γ is the clustering parameter. The δ equals 1 when $x_i = x_j$, and 0 otherwise.

In Section 3, we focus on the study design, and in Figure 2, we visually present the next structure of the study and part of the methodology principles overview.

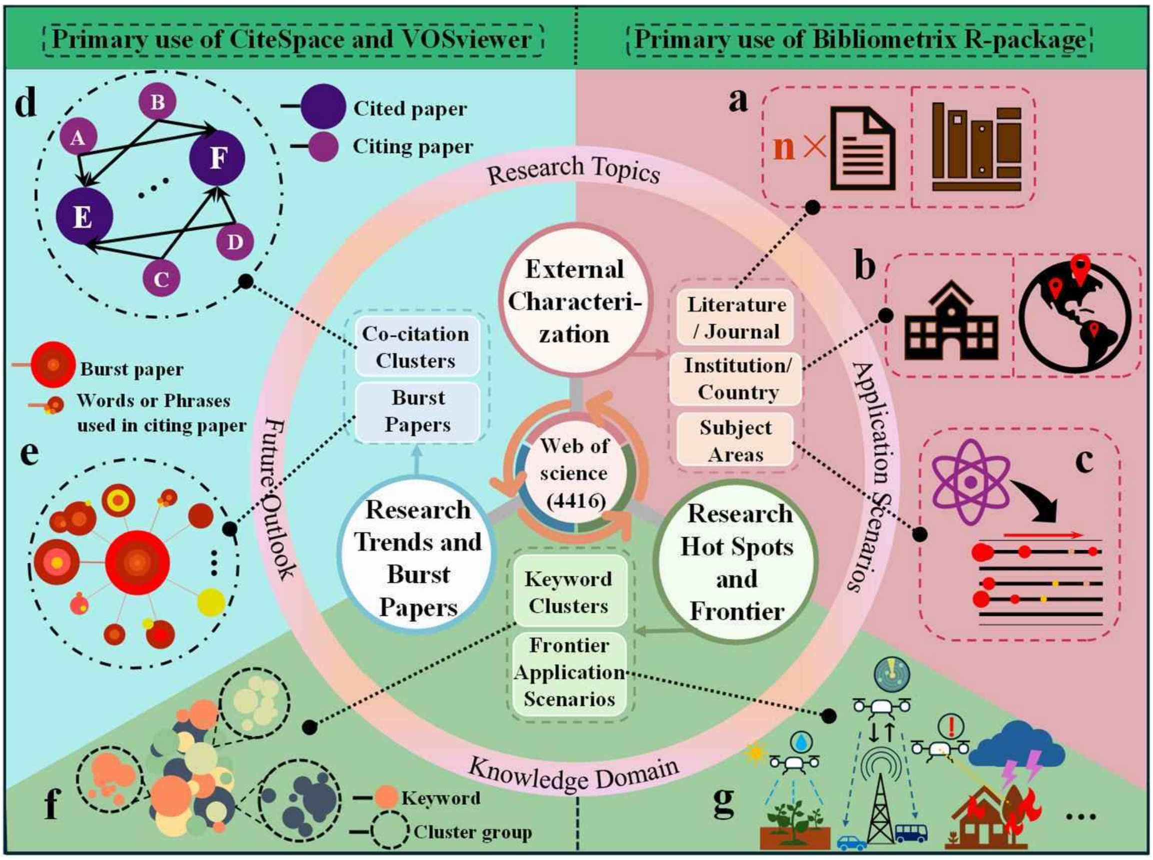


Figure 2. Research methodology and structure. Note: Of the three colors in the main body of Figure 2, the pink area represents Section 4, the cyan area stands for Section 5, and the green area on behalf of Section 6. Figure (**a**–**g**) each represent the content or principle in each subsection, and the text in the black dashed box at the top describes the main tools used, i.e., Figure (**d**–**f**) mainly use CiteSpace and VOSviewer, and Figure (**a**–**c**) mainly use the Bibliometrix R packages.

4. External Characterization

4.1. Number and Sources of Publications

We compressed the plain text files of the sample literature and imported them into Bibliometrix R packages, which can obtain external features, such as the number of annual publications, the number of journal publications, and the cumulative number of occurrences, based on the data which we analyzed.

The annual publication volume provides an overview of the evolution and progress of a research field. As shown in Figure 3, the overall trend in publication volume and cumulative journal occurrences in the field of UAV path planning from 2000 to 2024 has been upward. A total of 4416 publications were identified, with the year 2018 serving as a dividing point. After 2018, there was a significant surge in the number of publications, with papers published between 2019 and 2024 accounting for 74.864% of the total. This suggests that UAV path planning has attracted increasing attention from the academic community in recent years, reflecting its promising research prospects.

Figure 4 presents key information from the Bibliometrix R package overview interface. The average annual growth rate of publications from 2001 to 2024 was 26.28% (The number of publications in 2000 was zero, as shown in Figure 3, and is thus not included in the statistics). A total of 1532 sources and 9745 authors contributed to the literature, with international co-authorship accounting for 22.33%. This indicates that UAV path planning is a broad field with substantial involvement from researchers and research institutions worldwide.

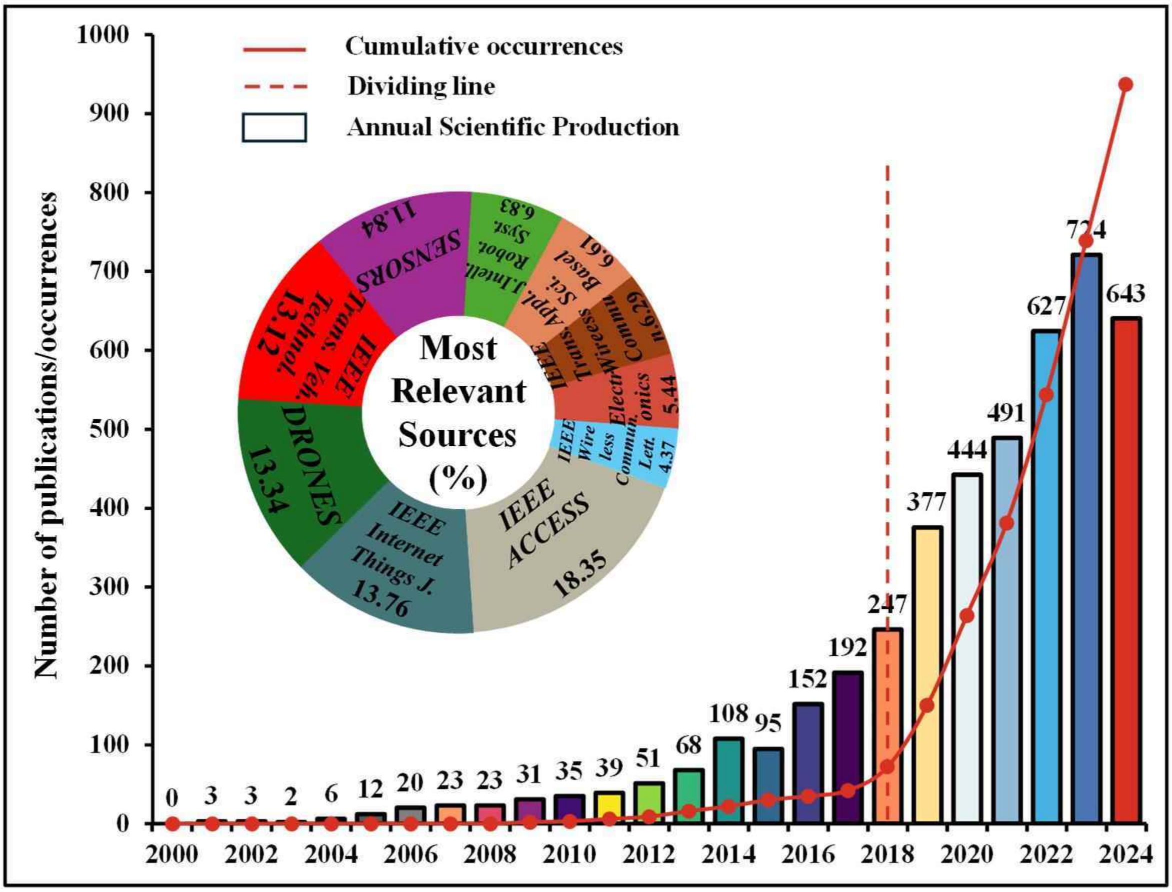


Figure 3. Distribution of publications and sources, 2000–2024. Note: The abbreviation of journal names follows the ISO 4 standard.

Figure 4. The main information on sample literature from the Bibliometrix R package.

The dataset includes 2621 journal papers, 1730 conference papers, and 65 reviews, with the proportion of reviews being only 1.472%. This relatively low percentage of reviews highlights two points: first, there is a lack of systematic reviews in the field of UAV path planning; and second, the strong interdisciplinary nature of UAV path planning makes it challenging to integrate research and application results from various domains.

In addition, the number of publications and the co-citation frequency of source journals are crucial indicators of a journal's academic impact. We examined the top 10 journals with the highest number of publications in the field of UAV path planning from 2001 to 2024, as detailed in Table 2.

Table 2. Statistics on the information of TOP 10 sources.

Source	Number	IF	H-Index	JCR	Co-Citation Frequency	Found Year
IEEE Access	172	3.7	56	Q2	3582	2013
IEEE Internet of Things Journal	129	9.0	47	Q1	3194	2014
Drones	125	4.8	43	Q1	2649	2017
IEEE Transactions on Vehicular Technology	123	6.5	146	Q1	3173	1952
Sensors	111	3.7	132	Q2	1572	2001
Journal of Intelligent & Robotic Systems	64	3.2	62	Q2	1755	1988
Applied Sciences-Basel	62	2.7	23	Q2	1569	2011
IEEE Transactions on Wireless Communications	59	8.6	186	Q1	3895	2002
Electronics	51	2.6	21	Q2	1327	2012
IEEE Wireless Communications Letters	41	4.9	46	Q1	1502	2012

Note: In Table 2, IF is based on the data from the last five years.

These 10 journals published a total of 937 papers, accounting for 21.218% of the total number of publications. Among them, IEEE Access published the highest number of papers (172), representing 18.356% of the publications from the top 10 journals. In terms of co-citation frequency, IEEE Transactions on Wireless Communications had the highest count (3895), accounting for 16.083% of the total co-citations, closely followed by drones (125/2649).

Two key academic metrics are presented in Table 2: the impact factor (IF) and the H-index, which are used to measure a journal's academic impact comprehensively [85,86]. Among the top 10 journals, three have an Impact Factor greater than 5.0, and five are classified in the Q1 JCR partition. These include leading international academic journals and authoritative conferences in fields such as intelligent robotics, the Internet of Things (IoT), wireless communications, and aerospace engineering. Notably, six of these journals were established after 2010, indicating that the field of UAV path planning has undergone rapid development and expansion in terms of academic influence, research depth, and breadth.

Cumulative occurrences of journal publications are an important metric for identifying major publishing platforms within a field. Using the Bibliometrix R package, we obtained data on the production of the top 10 journals from 2008 to 2024, as shown in Figure 5. The Journal of Intelligent & Robotic Systems was a major publishing platform from 2009 to 2018. However, journals such as IEEE Internet of Things Journal (2014) and Drones (2017) have experienced rapid growth since their inception. These journals have shown a significant increase in cumulative occurrences and have become key journals in the field of UAV path planning in recent years.

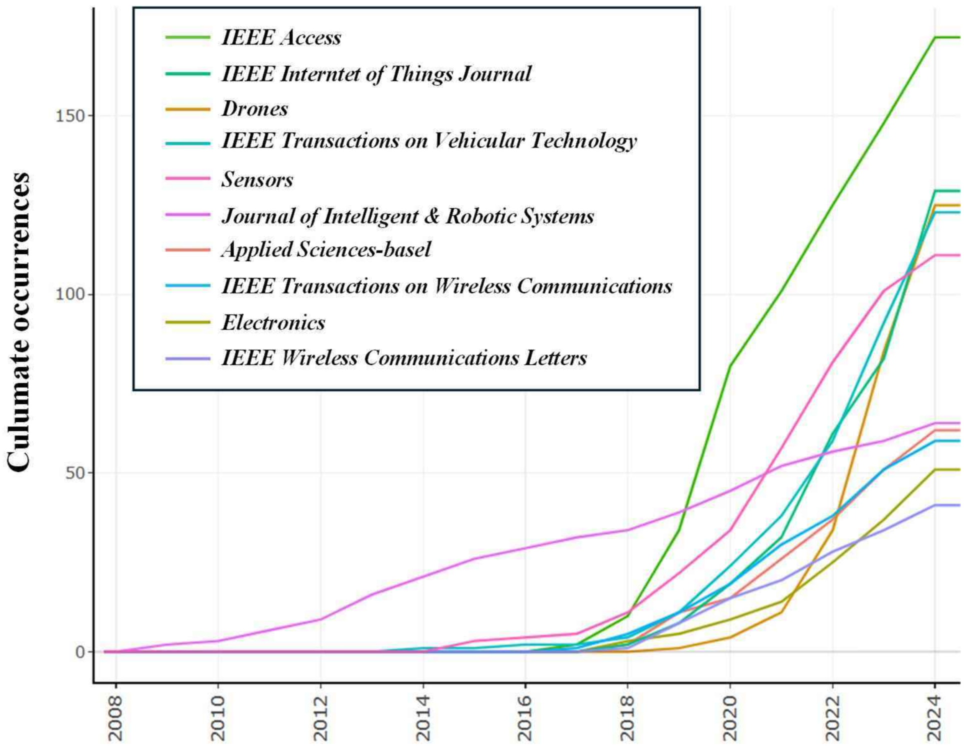


Figure 5. The most 10 sources' cumulative occurrences, 2008–2024. Note: Each color line represents a journal, and the journals within the solid black box are sorted from top to bottom by cumulative occurrences in 2024.

4.2. Institution and Country/Region Statistics

Based on the data of Bibliometrix R packages, a total of 1858 institutions around the world have published papers in the field of UAV path planning from 2001 to 2024, and the large number of research institutions and the base number of publications indicates that the field is more active. Among them, there are 776 institutions with only 1 publication, accounting for 41.765%, and 786 institutions with 3 or more publications, accounting for 42.304%, with an average of 2.37 publications by the institutions (which is a low to medium level compared to the field of computer science), the average number of publications is low, and the low number of publications accounts for a large percentage of the institutions, which is presumed to be due to the uneven distribution of the research resources, or due to the large coverage of the research field, with different institutions focusing on different subfields, resulting in a lack of cooperation among institutions. In the future, there is a need to further optimize the allocation of research resources among institutions and to carry out extensive interdisciplinary cooperation. Table 3 lists the top 15 institutions in terms of the number of publications in the field of UAV path planning, with a total of 1687 publications, accounting for 38.202% of the total number of publications; among them, there are 8 institutions with more than 100 publications. From a national level, the majority of the top institutions are located in China, indicating that China has relatively concentrated its research power in this field, and formed a group of core institutions with high research outputs. Similarly, the contributions of research institutions in other countries are also significant. They have explored different directions in UAV path planning, thereby expanding the interdisciplinary scope of this field.

Table 3. Statistics on the information of TOP 15 issuing institutions.

R	Issuing Institutions	Number
1	Beihang University	244
2	Northwestern Polytechnical University	183
3	Chinese Academy of Sciences	160
4	Nanjing University of Aeronautics and Astronautics	150
5	Beijing Institute of Technology	139
6	National University of Defense Technology	111
7	Southeast University	111
8	Beijing Univ of Posts and Telecommunications	105
9	Xidian University	73
10	University of Electronic Science and Technology	71
11	Harbin Institute of Technology	70
12	University of New South Wales	70
13	Centre National de la Recherche Scientifique	69
14	National University of Singapore	66
15	United States Department of Defense	65
	Sum	1687

We delve further into the institutions in Table 3 and find that Beihang University's School of Automation Selence and Electrical Engineering and School of Aeronautic Science and Engineering have made significant progress in the field of multi-rotor UAV cluster formation control [51,87,88], and Northwestern Polytechnical University has achieved innovative results in the research of UAV coverage path planning and distributed cooperative control [89–92], the Institute of Automation (IAS) of the Chinese Academy of Sciences is more prominent in the field of UAV remote sensing [93–96]. There are also some noteworthy research institutions, such as the National University of Singapore (NUS), which has been widely recognized by domestic and international academics in the field of UAV wireless network communication [97–99]. The University of New South Wales has been developing rapidly in the field of UAV inspection [100–103]. The United States Department of Defense is at the forefront of research in UAV swarm control [104–106]. Centre National de la Recherche Scientifique has deeply practiced in UAV mobile edge computing and its applications [107–109].

The spatial statistical analysis of publication counts reflects the level of attention and research activity in the field of UAV path planning across different countries or regions. By analyzing the publishing institutions, further measurement and visualization of the country/region distribution can provide insights into the relationship between UAV path planning research, technological advancement, and the regional political and economic landscape. Figure 6 illustrates the country/region distribution (2000–2024) and frequency of occurrence (2014–2024). Due to the significant proportion of international co-authorship in the literature, a single publication may be associated with multiple countries. Consequently, the total number of country distributions detected exceeds the total number of sample publications (5768/4416). The countries with the top 10 distributions and their respective centralities are as follows: China (2489/0.35), the United States (597/0.31), Republic of Korea (597/0.31), China (597/0.31), the United Kingdom (194/0.18), Canada (183/0.06), Australia (179/0.04), India (159/0.14), Germany (122/0.13), France (111/0.12), and Singapore (102/0.02).

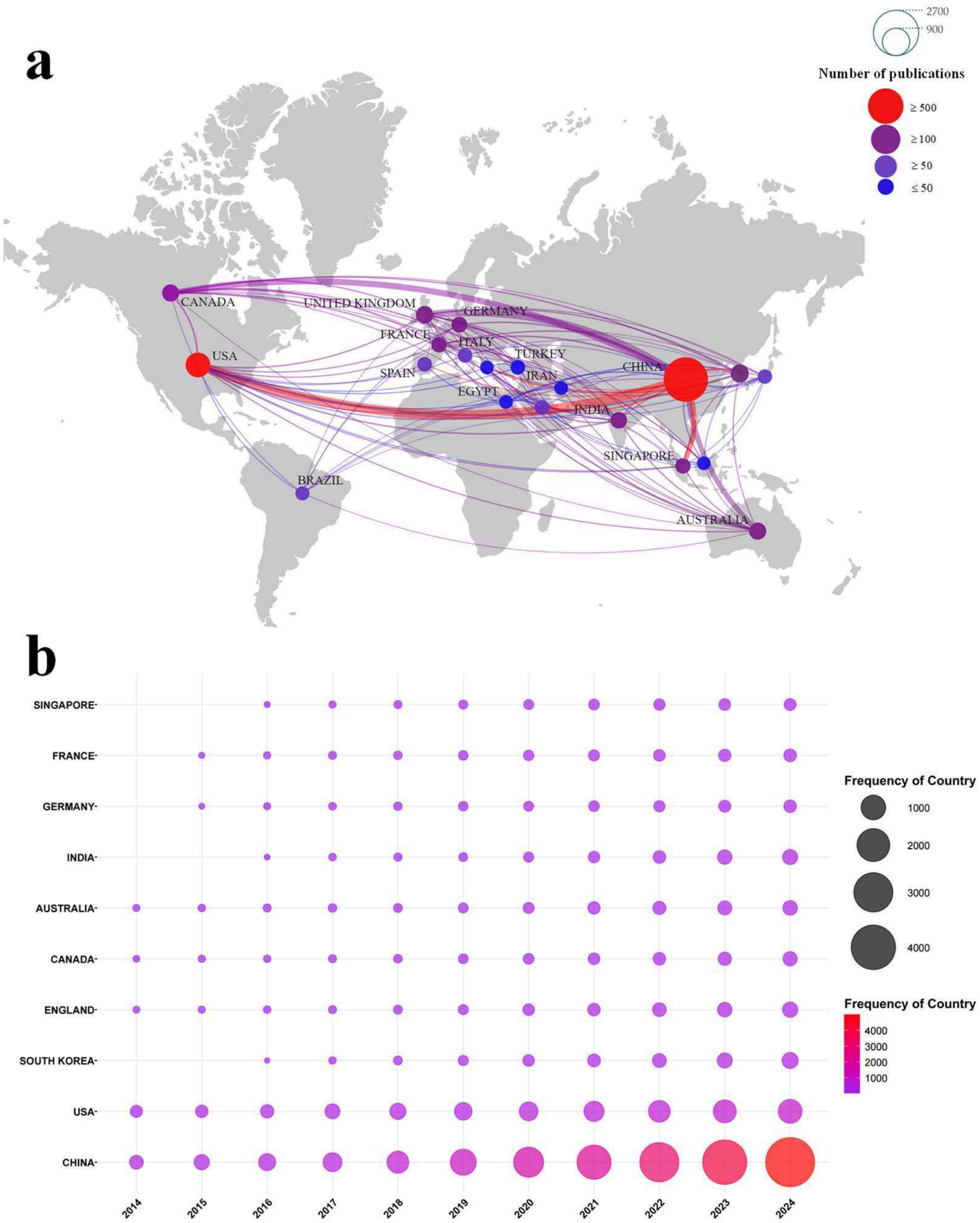


Figure 6. (**a**) Distribution of publications by country/region, 2000–2024; (**b**) Frequency of occurrence of country/region, 2014–2024.

We observe that China accounts for more than half of the total number of publications (56.36%) and exhibits the highest centrality score (0.35), positioning itself as the primary leader and driving force in UAV path planning research. This dominance is largely attributable to a series of supportive policies and market demand within China, with the United States followed closely (597/0.31). Notably, aside from Europe and the United States, where UAV R&D has been well established, countries such as Republic of Korea, India, and Singapore also demonstrate a significant number of publications. This trend can be largely attributed to national policies that support the UAV industry, providing a substantial platform for UAV path planning research and facilitating the practical application and commercialization of research findings. These observations indicate that nations are collectively optimistic about the future applications of UAV.

International cooperation plays a crucial role in the field of high-precision technology. Figure 7 depicts a two-way chord diagram illustrating inter-country cooperation, with 90 countries/regions participating in UAV path planning research, where China stands out with the highest frequency of international collaboration, having cooperated 700 times with 50 countries, with primary partners being the United States (133), the United Kingdom (109), Canada (77), and Singapore (66), followed by Australia (64), such as [110–113]. The second is the United States, engaged in 324 collaborations with 44 countries, such as [114–116], while the United Kingdom (228), Canada (164), and Australia (155) have also formed numerous research partnerships. These data highlight the global and multidimensional development of UAV path planning research. Among these nations, China and the United States are central nodes in both technological development and international cooperation.

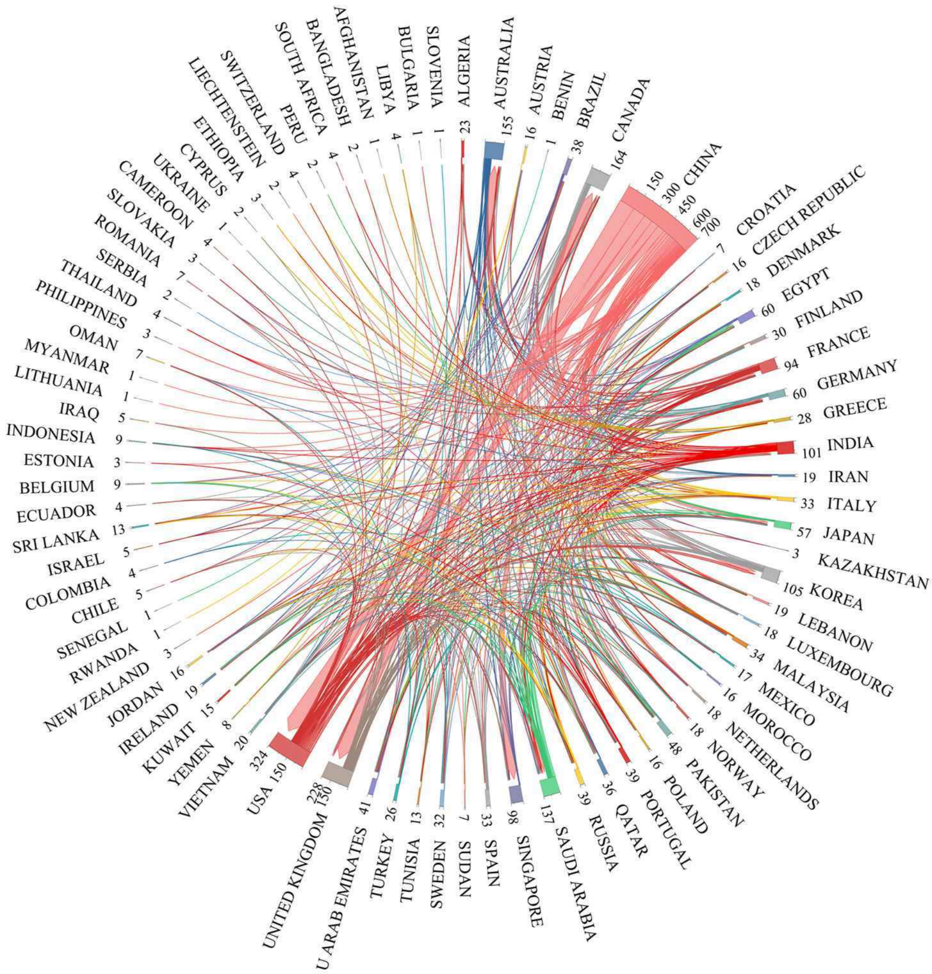


Figure 7. Two-way chord diagram of country/region cooperation.

4.3. Subject Areas Statistics

Based on the data obtained from CiteSpace's category co-occurrence analysis, Figure 8 provides an overview of the ten primary subject areas in UAV path planning research (N = 58, E = 225, Q = 0.318, S = 0.7669). The horizontal coordinates from 1 to 10 correspond to the following subject areas:

Engineering (2590; 0.62);
Computer Science (1733; 0.38);
Telecommunications (1285; 0.09);
Automation & Control Systems (789; 0.34);
Robotics (445; 0.11);
Remote Sensing (277; 0.17);

Transportation (235; 0.32);
Instruments & Instrumentation (206; 0.17);
Chemistry (173; 0.05);
Operations Research & Management Science (143; 0.06).

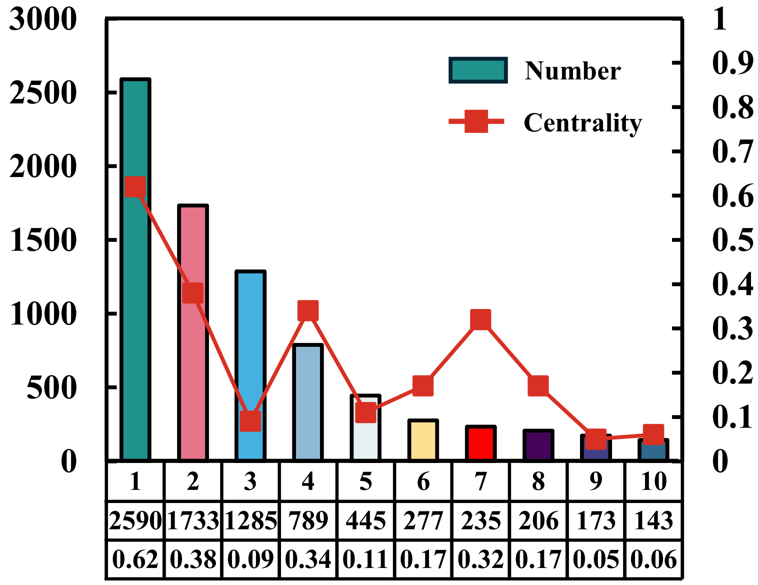


Figure 8. Main subject areas covered by UAV path planning.

We can see that the research on UAV path planning predominantly spans the fields of Engineering, Automation & Control Systems, and Computer Science. Among these, Engineering has the highest number of publications (2590) and the largest mediated centrality score (0.62), followed by Computer Science (1733; 0.38). This can be attributed to the significant overlap between UAV path planning and key subfields within Engineering, including Mechanical, Electrical, and Aerospace Engineering, as well as the integration of artificial intelligence (AI), machine learning, computer vision, and optimization algorithms within Computer Science. In contrast, the Chemistry field exhibits the lowest centrality score (0.04), which can be explained by the relatively weak and indirect connection between Chemistry and UAV path planning, primarily concerning energy-related topics, such as battery technology. From the above data, we can conclude that UAV path planning is an interdisciplinary research area that intersects Engineering, Automation & Control Systems, and Computer Science, making it a complex problem that integrates hardware, software, and control technologies.

Figure 8 reveals the high-productivity and high-centrality subject areas in UAV path planning, presenting a static snapshot of the current landscape. However, the evolution and development of these fields are equally significant and merit further exploration. To gain a deeper understanding of the dynamic trends, we have employed CiteSpace's dual-map overlay and timeline functions to analyze the interconnections among disciplines and their evolutionary trajectories over time.

CiteSpace's dual-map overlay function is employed to compare and analyze network structures across different topics or periods. By overlaying two network layers, this method reveals the differences and correlations between them, thereby offering insights into paper distribution within a discipline, citation trajectories, and shifts in the center of gravity [73]. In the dual-map overlay, each node represents a journal. The map is divided into two parts: the left side indicates the cited journals, while the right side shows the citing journals. Citation links are represented by curves, which display the flow of citations between the journals. The trajectories of these citation links provide valuable insights into the cross-disciplinary relationships within the field. The Z-score's function highlights the strongest, most consistent citation trajectories, with thicker connecting lines indicating higher z-scores. Different colors of paths between journals in distinct disciplines indicate the direction of citations, i.e., papers in one field on the right are cited by journals in another field on the left [117].

We utilize the distribution of subject areas and the node association pattern observed in the dual-map overlay to track the evolution of nodes and examine changes in the research network. For specific information, please refer to Figure 9a.

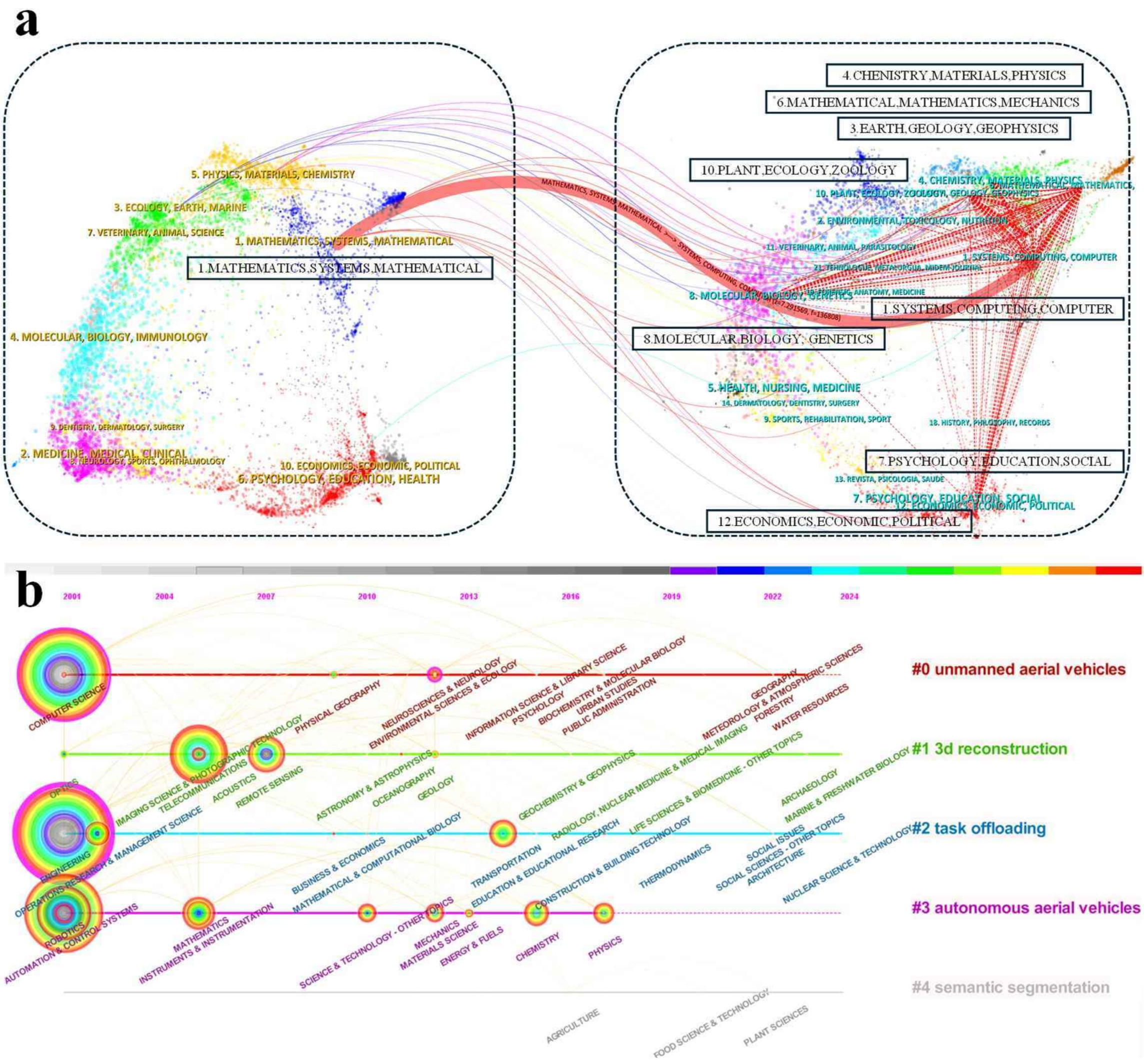


Figure 9. (**a**) Dual-map overlay; (**b**) Subject area timeline. Note: In Figure 9a, the black dashed boxes in the figure label the cited journals on the left and the citing journals on the right, and for greater clarity, the subject labels in the figure are shown in the black text box.

- Subject areas distribution pattern: As shown in Figure 9a, the literature from the fields of Systems, Computing, and Computer Science is notably influenced by literature from the fields of Mathematics, Systems, and Mathematical Sciences (z = 7.29, f = 136,808). This strong citation relationship highlights that Mathematics and Systems form the foundational basis of the UAV path planning field, which is more maturely developed. In contrast, Systems, Computing, and Computer Science are the current focal areas of UAV path planning research. These areas include advanced topics such as reinforcement learning, deep learning, control systems, computer vision & image processing, and networking & communication, along with applications in simulation & virtual reality.

- Node association pattern: As observed on the right-hand side of the citing journal, the fields of Earth, Geology, Geophysics, Chemistry, Materials, Physics, Mathematics, Mechanics, Psychology, Education, Social Sciences, Molecular Biology & Genetics, and Plant Ecology, Zoology, as well as Economics, Political Science, are closely interconnected. This indicates that the UAV path planning research field has extensive coverage, spanning multiple areas and applications.

CiteSpace's timeline function reveals the development and evolution trends in the field through the timeline and frequency of keyword appearances. The timeline begins in 2001, with a time interval of 3 years. The timeline graph of subject areas, shown in Figure 9b (Q = 0.7185, S = 0.9153, N = 58, E = 225), identifies the first five largest clusters, which represent at least 58 subject areas involved in UAV path planning research.

The five clusters in Figure 9b can be analyzed as follows:

#0 Unmanned aerial vehicles were closely associated with Computer Science initially, but, over time, their scope expanded to encompass Physical Geography, Neuroscience & Neurology, Environmental Science & Ecology, Information Science & Library Science, Biochemistry & Molecular Biology, Meteorology & Atmospheric Sciences, and Forestry, among others. This progression reflects the interdisciplinary nature of UAV path planning, with applications gradually moving from theoretical foundations in Computer Science and Physics to broader fields, such as Biology [118–120], Environmental Science [121,122], and Social Management [123,124]. This expansion promotes interdisciplinary cross-fertilization and provides innovative solutions to complex real-world problems.

#1 3D reconstruction [125] refers to the process of creating a three-dimensional model or representation of an object or scene from a two-dimensional image or other data sources. The primary objective is to generate a virtual model that can serve various purposes. The advancement of path planning techniques for aerial photography by UAVs is crucial for enhancing the quality and efficiency of 3D reconstruction [126]. Moreover, 3D reconstruction techniques offer detailed environmental models, which are essential in collaborative multi-UAV path planning [127]. These two techniques are complementary and collectively contribute to the growing application of UAVs across multiple fields. Initially, 3D reconstruction was introduced through Optics [128] and saw significant development after 2005, particularly in the fields of Imaging Science & Photographic Technology and Acoustic Remote Sensing [129]. Subsequently, it expanded into disciplines such as Astronomy & Astrophysics, Geology, Radiology, Nuclear Medicine & Medical Imaging [130–133]. Since 2022, 3D reconstruction has also found applications in Archaeology [134,135] and Marine & Freshwater Biology.

#2 Task offloading is a concept in computer science and networking, particularly relevant in mobile computing and cloud computing [136]. In the context of UAV path planning, task offloading refers to the transfer of computational tasks from resource-constrained devices (e.g., ground terminals) to UAVs, which possess greater computational capacity. This ensures that UAVs can efficiently service all terminals requiring computational resources [137]. Task offloading techniques are predominantly utilized in engineering, Operations Research & Management Science [138,139], and have been a focal point since 2013, particularly within the transportation sector. The technology also extends its influence in fields such as Business & Economics, Education, Construction & Building Technology, Thermodynamics, Social Sciences, and Nuclear Science & Technology [140–143].

#3 Autonomous aerial vehicles (AAVs), often referred to as UAVs with advanced autonomy control capabilities, are capable of performing complex tasks and making autonomous decisions in dynamic and challenging environments [144]. AAVs are closely linked to fields such as Robotics, Automation & Control Systems [145,146], and, as the knowledge domains evolve, increasingly intersect with Mathematics, Instruments & Instrumentation, Mechanics, Energy & Fuels, Chemistry, and Physics [147–150]. This expanding relationship underscores the growing interdisciplinary nature of UAV technology.

#4 Semantic segmentation is a computer vision technique that identifies and classifies different objects and scenes by classifying each pixel in an image through deep learning models [151]. This technique provides detailed environmental insights and intelligent decision support for UAV path planning. From the figure, it is evident that semantic segmentation technology was first applied in the field of Agriculture around 2015, later expanding its scope to include Food Science & Technology and Plant Sciences after 2019 [152–155].

In this section, by synthesizing the external characteristics of relevant literature, it is evident that UAV path planning has become a prominent area of international academic research. In terms of the annual publication volume, studies in this field have experienced rapid growth in recent years, particularly after 2018, when the number of related papers significantly increased. This growth spans multiple disciplines and application scenarios, fostering a cross-disciplinary research environment. This trend underscores the expanding demand for UAV path planning across diverse multidisciplinary applications in recent years.

5. Research Trends and Burst Papers

5.1. Co-Citation Clustering Analysis

Literature co-citation refers to the phenomenon where multiple papers are cited together by later studies. When these papers are frequently co-cited, it creates a co-citation relationship between them, indicating their relevance and influence in the field. Clustering, on the other hand, reflects the similarity of the content within these cited works, with papers that share more co-citations being more closely related. The analysis of a literature co-citation network allows researchers to explore the development and evolution of a specific research area.

Figure 10 presents the co-citation clustering network (Q = 0.7997, S = 0.9053), which combines research trends with the evolution of highly cited papers. The graph spans from 2001 to 2024 and shows an increase in the number of clusters, nodes, and connections between nodes across clusters (N variation in four trends: 162/341/557/624). This upward trend reflects the growing body of research in UAV path planning. By analyzing the co-citation clusters, we can summarize four main research trends in UAV path planning from 2001 to 2024.

- The first trend is “multi-objective cooperative control problems in cluttered natural environments”, which in chronological order are #9 target assignment (1; 58; 2002), #13 using multi-objective evolutionary algorithm (0.978; 29; 2005), #6 cluttered natural environment (0.972; 75; 2005).

The UAV multiobjective cooperative control problem can be divided into five subproblems: cooperative target assignment, coordinated UAV intercept, path planning, feasible trajectory generation, and asymptotic trajectory following [156], of which, #9 target assignment is an important research direction of cooperative control, which involves the concepts of vector field path tracking, precise landing and target localization, target tracking, obstacle detection and avoidance, and tail-seat aircraft control [157,158]. Initially focusing on the traditional topics of collision avoidance and formation flying, research on efficient computer vision and distributed control network computation topics was gradually carried out in the 21st century [159], such as the Defense Advanced Research Projects Agency (DARPA), the Fast Lightweight Autonomy (FLA) Program (2014), and the

X-61A Pixie UAV Program (2015), as well as the Ku-band UAV datalink (2016) developed by the Tenth Research Institute of China Electronics Technology Group Corporation and Adaptive UAV Target Detection Method for Stream-Guided Feature Aggregation (2024). #13 Using multiobjective evolutionary algorithm (MOEA) was first noticed in the mid-1980s for solving multi-objective optimization problems (MOPs), and with the dramatic increase in productivity levels, real-world engineering applications have seen a wide range of solving accuracy and speed for large-scale MOPs demand, numerous complex MOEAs emerged, such as decomposition-based MOEAs (MOEA/Ds), memetic MOEAs, coevolutionary MOEAs, selection and offspring reproduction operators, MOEAs with specific search methods, MOEAs for multimodal problems, constraint handling and MOEAs, computationally expensive multiobjective optimization problems, dynamic MOPs, noisy MOPs, and combinatorial and discrete MOP [160,161].

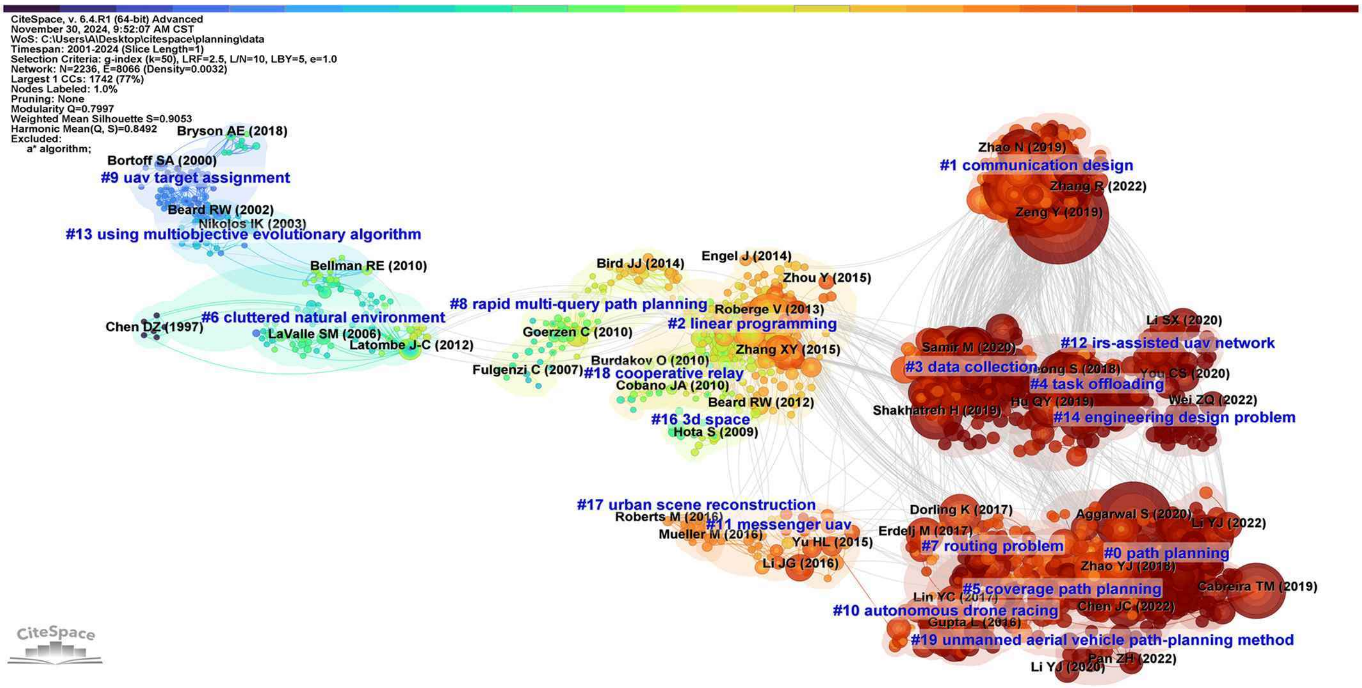


Figure 10. Co-citation clustering network. Note: Node size is proportional to the number of times the node has been co-cited, and the position of the clusters corresponds to the average year of the co-cited literature. The colors at the top of the figure represent time slices, from 2001 (dark blue) to 2024 (dark red). The most co-cited papers in each cluster are shown with their labels.

As far as the field of UAV path planning is concerned, MOEAs address two primary challenges: first, the utilization of offline planners for UAV navigation in known environments; and second, the implementation of online planners for UAV navigation in completely unknown environments. Recent advancements in the military domain have also introduced heterogeneous collaboration techniques, such as the heterogeneous clustering of multiple unmanned air and ground vehicles that have been developed in the military in recent years [162,163]. #6 Complex natural environment mainly focuses on the impact of various types of aviation meteorology on UAV operation and flight safety, including airframe icing caused by wind, clouds, precipitation, and dense fog, turbulence, downburst storms induced by thunderstorms, low-altitude wind shear, thermal updrafts, low visibility induced by dense fog, and flying in low-altitude scenarios facing complex jungle and mountain obstacle avoidance problems, these adverse weather conditions may also adversely affect the UAV's endurance, sensors used for navigation and collision avoidance [164,165]. Optimization for a cluttered natural environment involves multiple disciplines of Aerodynamics, Fluid Dynamics, Structural Mechanics, Materials Science, and Mechanical Engineering at the hardware design layer, while the software layer is mainly concerned with model and algorithm design for specific environment models to improve the UAV's flight control and situational awareness capabilities. For example, Bencatel R et al. studied wind shear models, including surface, layer, and ridge wind shear models, and Fu Y et al. studied thermal updraft models, including chimney models and bubble thermal models [166,167].

- The second trend is "high-performance UAV obstacle avoidance technology", including #8 rapid multi-query path planning (0.977; 70; 2009), #18 cooperative relay (0.998; 16; 2009), #16 3d space (0.993; 21; 2009), #2 linear programming (0.916; 234; 2012).

The first clustering #8 rapid multi-query path planning (RMQPP) belongs to the same robot motion planning problem as single-query path planning (SQPP), compared with SQPP represented by RRT, RMQPP is an algorithm that can quickly respond to multiple-path queries and usually builds a global roadmap in the preprocessing stage so that it can be reused in multiple queries. RMQPP mainly plays a navigational role in robotics, autonomous driving, and virtual simulation. UAV guidance requires consideration of dynamics, 3D environment, disturbed operating conditions, and state knowledge uncertainty, so RMQPP is closely related to #16 3D space and #2 linear programming. Early RMQPP utilized the raster method and Voronoi diagrams for solution [168], and in recent years, mixed-integer linear programming (MILP) has been widely applied to UAV path planning problems, and related research are road network-based multi-query path planners using quasi-randomized Hammersley set for placing samples in a four-dimensional configuration space, as well as bridge-testing algorithm for discrete rescue [169–172].

#18 Collaborative relay refers to the relaying of information between UAVs through collaboration, and airborne relaying can extend wireless sensor networks (WSNs) to remote terrains, which is particularly important for improving UAV communication capabilities in remote areas or complex environments [173]. Among them, intelligent heterogeneous architecture utilizing UAVs are considered a new paradigm with great potential to facilitate the three central usage scenarios of future wireless networks, i.e., bandwidth-consuming eMBB, URLLC, and mMTC, with a clear role in providing network service restoration in disaster-stricken areas, augmenting public safety networks, or dealing with other emergencies that require URLLC. On a mathematical level, the selection of the location of the communication relay nodes in the presence of obstacles is essentially a multipole problem, which requires an approximation of the global minimum to be found in the optimal placement problem of the communication relay nodes, which guarantees the success rate while considering the lifetime of the network, and the key constraints of the problem include lossy on-board channels for the UAVs and the finite power, which remain the key challenges for the emergence of 5G and 5G beyond (B5G) the main challenges [174,175].

- The third trend is defined as "intelligent path planning and scene reconstruction in urban environments" and includes #11 messenger UAV (0.968; 42; 2014), #17 urban scene reconstruction (1; 17; 2015), #7 routing problem (0.913; 71; 2017), #10 autonomous drone racing (0.946; 54; 2018), #5 coverage path planning (0.939; 75; 2018), #0 path planning (0.835; 282; 2019) #19 unmanned aerial vehicle path-planning method (0.978; 16; 2021).

All of these clusters appeared after 2014, when UAV intelligent path-planning techniques significantly evolved, with the emergence of advanced hybrid algorithms such as short-term dynamic windowed obstacle avoidance (UAV_DPPA_DWA) [176], a multi-agent system for automated clustering with self-optimization (MASAC) [177] and adaptive heuristic path-planning (AHPP) [178]. In addition, machine learning and deep learning-based algorithms such as deep reinforcement learning, convolutional neural networks (CNNs), and generative adversarial networks (GANs) are also fully applied, such as the CityGaussian algorithm (2024) proposed by the Pattern Recognition Laboratory of the Institute of Automation of the Chinese Academy of Sciences [179]. In urban environments, UAV applications have been expanded in fields such as photography, surveillance, mapping, urban planning, infrastructure management, disaster prediction, assessment, and response [180–186] involving key technologies such as computer vision, GIS, radar detection, and other key technologies, such as the Imperial College London and National University of Ireland, Maynooth (ICL-NUIM) dataset for evaluating the use of RGB-D data for visual odometry, 3D reconstruction, and slam algorithms for surface reconstruction accuracy [187–191].

After sorting the clusters according to their appearance time, it is found that #11 messenger UAV, #7 routing problem, #10 autonomous drone racing, and #5 coverage path planning have similar labels, but the focus of each cluster is different. The #11 messenger UAV tends to play the role of "messenger" in air-ground coordination, transferring information between UAVs and UGVs, and focuses more on the role of communication relay. #10 autonomous drone racing Autonomous Drone Racing (ADR) is a technical competition focusing on the areas of intelligent perception, positioning and navigation, and autonomous control of UAVs. The emergence of the sport of drone racing occurred in 2014, with the first ADR being launched at IEEE IROS 2016, and held at IROS 2017, 2018, and 2019. Inspired by this competition, other international competitions emerged: the AlphaPilot, organized by Lockheed Martin in partnership with the Drone Racing League, and the Drone Game, organized by Microsoft and Stanford University. Some teams proposed novel solutions for on-board processing based on graphics processing units (GPUs), field programmable gate arrays (FPGAs), microcontrollers, and embedded computers such as Odroid or Intel Stick computers [192]. #5 Coverage path planning (CPP) emphasizes the complete coverage of the work area, i.e., the path needs to traverse the entire area within the work area except for obstacles, and tries to avoid the duplication of paths and shorten the travel distance. It is widely used in tasks that require coverage of large areas, such as cleaning robots, agricultural robots, and environmental monitoring [116,193]. The #7 routing problem focuses on planning a route for a group of UAVs or vehicles involving multiple starting and ending points, considering constraints such as capacity, time window, etc., and can be viewed as a MUTAPP problem [194].

- The fourth trend is summarized as "efficient communication and trajectory optimization for UAV networks", which includes five clusters that have emerged in the last decade: #1 communication design (0.857; 277; 2018), #3 data collection (0.854; 169; 2020), #4 task offloading (0.89; 115; 2020), #12 irs-assisted UAV network (0.956; 37; 2020), and #14 engineering design problem (0.985; 26; 2021).

In five clusters, #3 data collection is the basis for realizing intelligent decision-making and network management, including collecting environmental data, sensor data, task execution data, etc., to provide data support for UAV path planning. In the construction of modern smart cities, wireless communication systems, including UAVs, are expected to provide cost-effective wireless connectivity for devices without infrastructure coverage to reduce risks and costs [195]. Among them, intelligent low-altitude UAVs have become a primary research focus in this field. These UAVs rely on wireless technologies and intelligent sensing devices to collect data, which are integrated into IoT systems and transmitted to a central controller (CC) for further processing and decision-making. This enables the realization of a range of automated operations, including civil infrastructure inspection, cargo delivery, precision agriculture, wireless coverage, and security surveillance [196–198]. The use of UAVs for highspeed wireless communications is expected to play an important role in future communication systems; compared to high altitude platform (HAP)-based communications, UAV-based low altitude platforms (LAPs) are cheaper, faster to deploy, more flexible to configure, and have better communication channels due to the presence of short-range line-of-sight (LOS) links. Adaptive communication can also be used to jointly design paths with UAV movement control to give corresponding energy-saving trajectory schemes to further improve communication performance [97].

In summary, we give four trends in UAV path planning, the first trend emphasizes the use of cooperative control methods to solve the problem of anti-jamming of multiple UAVs in complex natural environments, the second trend focuses on solving the road network problem involving real-time planning of multiple paths for UAVs in 3D environments, the third trend primarily concentrates on discussing the applications of UAV path planning in the context of urban construction., and the fourth trend highlights the problem of energy-efficient trajectory optimization for intelligent low-altitude UAVs based on data collection.

5.2. Burst Papers Analysis

In CiteSpace, burst refers to a sudden and significant increase in the frequency of a variable (such as keywords or the number of citations to a particular paper) over a specific period. These bursts often signal deeper shifts or emerging trends within a research field. A "burst in paper" signifies a spike in the citation count of a particular work over a relatively short time, which typically indicates touching on a common academic concern.

In this analysis, the threshold was set to 100 in CiteSpace, and Figure 11 illustrates the results of the co-citation analysis network (N = 1325, E = 4830), highlighting 10 major co-citation papers. The specifics of these clusters are provided in Table 4.

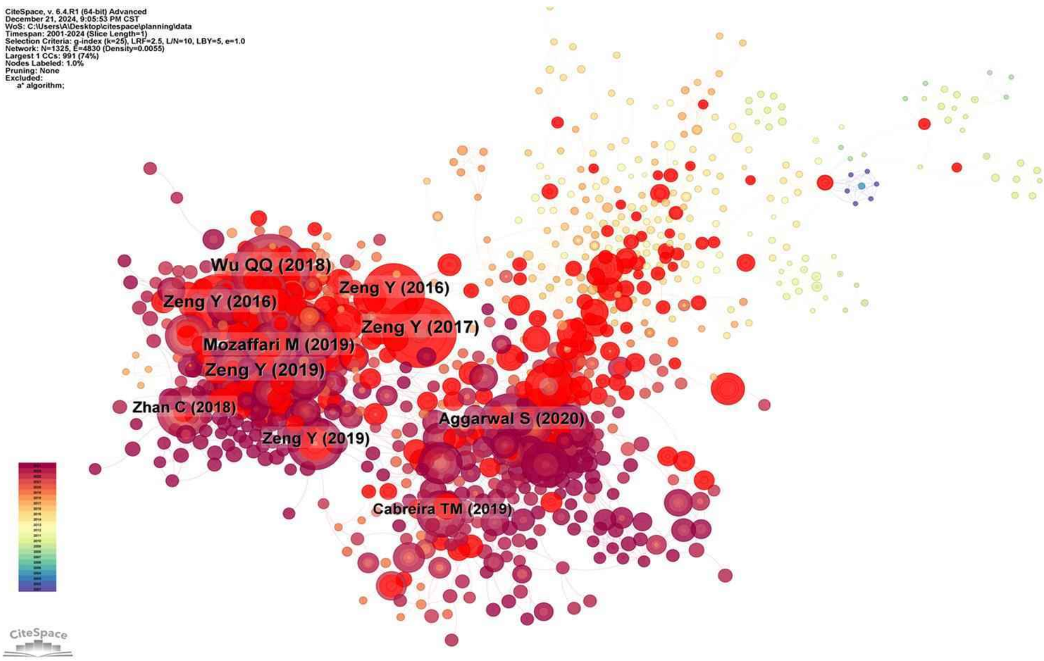


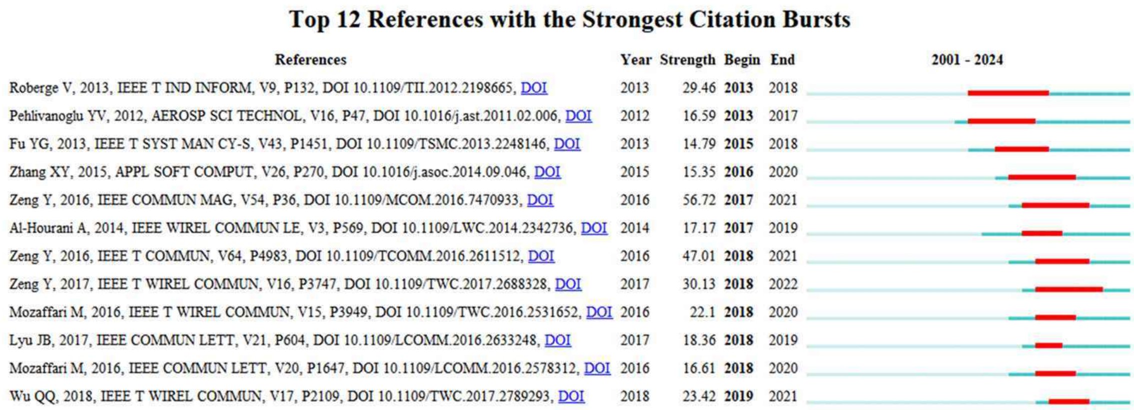
Figure 11. Co-citation burst network. Note: Black labels are shown for authors and publication times, and burst is shown as a red color spreading from the center of the node's circle to its circumference; the greater the burst intensity, the higher the red coverage.

Table 4. Top 10 most co-cited papers, 2001–2024.

R	C	Co-Citation	Title	T	C/Y	S	B
1 [199]	2599	195	Wireless communications with unmanned aerial vehicles: Opportunities and challenges	2016	324.88	IEEE Communications Magazine	Y (56.721)
2 [97]	993	161	Throughput Maximization for UAV-Enabled Mobile Relaying Systems	2016	124.13	IEEE Trans. Commun.	Y (47.007)
3 [98]	1474	227	Energy-Efficient UAV Communication with Trajectory Optimization	2017	210.57	IEEE Trans. Wireless Commun.	Y (30.131)
4 [200]	516	122	Energy-Efficient Data Collection in UAV Enabled Wireless Sensor Network	2018	86	IEEE Wireless Communications Letters	Y (6.614)
5 [99]	1304	258	Joint Trajectory and Communication Design for Multi-UAV Enabled Wireless Networks	2018	217.33	IEEE Trans. Wireless Commun.	Y (23.423)
6 [201]	1114	289	Energy Minimization for Wireless Communication with Rotary-Wing UAV	2019	222.8	IEEE Trans. Wireless Commun.	N
7 [202]	867	126	Accessing From the Sky: A Tutorial on UAV Communications for 5G and Beyond	2019	173.4	Proc. IEEE	Y (6.584)
8 [203]	1590	176	A Tutorial on UAVs for Wireless Networks: Applications, Challenges, and Open Problems	2019	318	IEEE Commun. Surv. Tutorials	N
9 [204]	268	104	Survey on Coverage Path Planning with Unmanned Aerial Vehicles	2019	53.6	Drones	N
10 [10]	620	168	Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges	2020	155	Comput. Commun.	N

Note: Papers in Table 4 are sorted by time of publication, and the citation counts of the papers were sourced from WoS. In column B, Y indicates that the paper is a burst paper and gives burst strength, and N stands for the paper is not a burst paper. Abbreviations in Table 4: R (rank and reference); C (citations); T (time); C/Y (citations/year); S (source); B (whether or not it is a burst node).

Using CiteSpace's burst function, we set the minimum duration to 2 and the mutation monitoring sensitivity value γ to 0.75. This configuration allowed us to identify the 12 references with the strongest citation bursts, as shown in Figure 12. Among these, 11 references exhibited a burst strength of more than 15, and 5 references had a burst strength exceeding 25. Additionally, seven of these references experienced bursts lasting for three years or more.


Top 12 References with the Strongest Citation Bursts

References	Year	Strength	Begin	End	2001 - 2024
Roberge V, 2013, IEEE T IND INFORM, V9, P132, DOI 10.1109/TII.2012.2198665, DOI	2013	29.46	**2013**	2018	
Pehlivanoglu YV, 2012, AEROSP SCI TECHNOL, V16, P47, DOI 10.1016/j.ast.2011.02.006, DOI	2012	16.59	**2013**	2017	
Fu YG, 2013, IEEE T SYST MAN CY-S, V43, P1451, DOI 10.1109/TSMC.2013.2248146, DOI	2013	14.79	**2015**	2018	
Zhang XY, 2015, APPL SOFT COMPUT, V26, P270, DOI 10.1016/j.asoc.2014.09.046, DOI	2015	15.35	**2016**	2020	
Zeng Y, 2016, IEEE COMMUN MAG, V54, P36, DOI 10.1109/MCOM.2016.7470933, DOI	2016	56.72	**2017**	2021	
Al-Hourani A, 2014, IEEE WIREL COMMUN LE, V3, P569, DOI 10.1109/LWC.2014.2342736, DOI	2014	17.17	**2017**	2019	
Zeng Y, 2016, IEEE T COMMUN, V64, P4983, DOI 10.1109/TCOMM.2016.2611512, DOI	2016	47.01	**2018**	2021	
Zeng Y, 2017, IEEE T WIREL COMMUN, V16, P3747, DOI 10.1109/TWC.2017.2688328, DOI	2017	30.13	**2018**	2022	
Mozaffari M, 2016, IEEE T WIREL COMMUN, V15, P3949, DOI 10.1109/TWC.2016.2531652, DOI	2016	22.1	**2018**	2020	
Lyu JB, 2017, IEEE COMMUN LETT, V21, P604, DOI 10.1109/LCOMM.2016.2633248, DOI	2017	18.36	**2018**	2019	
Mozaffari M, 2016, IEEE COMMUN LETT, V20, P1647, DOI 10.1109/LCOMM.2016.2578312, DOI	2016	16.61	**2018**	2020	
Wu QQ, 2018, IEEE T WIREL COMMUN, V17, P2109, DOI 10.1109/TWC.2017.2789293, DOI	2018	23.42	**2019**	2021	

Figure 12. Top 12 references with the strongest citation bursts. Note: Figure 12 sorts the references by the year in which the burst begins, with the red section indicating the time range of this burst. The strength value represents the popularity of the reference during that specific period. The 12 references associated with Figure 12 are as follows: [205], [206], [167], [207], [199], [208], [97], [98], [209], [210], [211], and [99], respectively.

The document with the highest burst strength is titled "Wireless communications with unmanned aerial vehicles: Opportunities and challenges", published in IEEE Communications Magazine (2016), with a burst strength of 56.72 [199]. This is closely followed by the same title, published in IEEE Transactions on Communications, with a burst strength of 56.72. Another notable paper is "Throughput maximization for UAV-enabled mobile relaying systems" (2016), with a burst strength of 47.01 [97]. The longest-lasting burst is from the paper "Comparison of Parallel Genetic Algorithm and Particle Swarm Optimization for Real-Time UAV Path Planning", published in IEEE Transactions on Industrial Informatics. This burst persisted for five years, from 2013 to 2018 [205]. The most recent burst is "Energy-efficient UAV communication with trajectory optimization" by Zeng et al., published in IEEE Transactions on Communications (2017), which lasted for four years, from 2018 to 2022 [98].

By integrating the highest co-citation papers (Table 4) with the strongest burst references (Figure 12), we observe four overlapping papers that exhibit both a high co-citation count and strong citation burst. This dual prominence underscores a strong correlation between co-citation and burst in the field. The four papers in question:

1. "Wireless Communications with Unmanned Aerial Vehicles: Opportunities and Challenges" (2016) [199]
2. "Throughput Maximization for UAV-Enabled Mobile Relaying Systems" (2016) [97]
3. "Energy-Efficient UAV Communication with Trajectory Optimization" (2017) [98]
4. "Joint Trajectory and Communication Design for Multi-UAV Enabled Wireless Networks" (2018) [99]

Below, we examine these four particular papers. In [199], Zeng et al. provides a comprehensive overview of UAV-aided wireless communications. The paper begins by introducing the networking architecture, which includes control and non-payload communication (CNPC) links for safe UAV operation, as well as data links for mission-related communications. The authors detail the channel characteristics of UAV-ground and UAV-UAV links, highlighting their unique features, such as LoS dominance, and potential issues, such as airframe shadowing. Key design considerations are discussed, including UAV path planning, where the optimal path depends on the specific application and is subject to various constraints. The study also explores energy-aware deployment and operational strategies to address the energy limitations of UAVs. Furthermore, the application of multiple-input multiple-output (MIMO) in UAV systems is analyzed, considering both its challenges and potential solutions.

In [97], Zeng et al. investigate a novel mobile relaying system using UAV-mounted relays. They formulate a throughput maximization problem, considering relay trajectory and power allocations for both source and relay, subject to mobility and information-causality constraints. For a fixed relay trajectory, the study identifies an optimal power allocation with a "staircase" water-filling structure. When channel gains change monotonically, this formulation reduces to the classic water-filling solution. Given power allocations, the relay trajectory is optimized through successive convex optimization, maximizing a lower bound of throughput. The study reveals the unique power allocation structure in mobile relaying. The proposed algorithms effectively improve throughput, and the analytical solution for a special case provides theoretical insights. Numerical results demonstrate that mobile relaying outperforms static relaying, underscoring the potential of UAV-enabled mobile relaying to enhance wireless communication performance.

Ref. [98] delves into energy-efficient UAV communication through trajectory optimization. Considering the UAV's propulsion energy consumption, it first formulates a model for the propulsion energy of fixed-wing UAVs based on flight parameters, such as speed and acceleration. The energy efficiency of UAV communication is then defined as the ratio of transmitted information bits to propulsion energy consumed. For unconstrained trajectories, the study finds that both rate-maximization and energy-minimization designs result in extremely low energy efficiency. A circular trajectory is subsequently proposed, with optimization of its radius and UAV speed to enhance energy efficiency. For constrained trajectories—considering factors such as initial and final states and speed limits—the authors develop an efficient algorithm based on discrete linear state-space approximation and sequential convex optimization. This algorithm provides valuable guidance for practical UAV communication systems.

In [99], Wu et al. focus on a multi-UAV-enabled wireless communication system. The main objective is to jointly optimize user scheduling and association, UAV trajectory, and transmit power to maximize the minimum average rate among all ground users in the downlink. The formulated problem is a mixed-integer, non-convex optimization problem. To solve this, the authors propose an iterative algorithm based on block coordinate descent and successive convex optimization. Initially, binary variables are relaxed, and then the variables are alternately optimized in each iteration. The key innovations of this work include: (1) the comprehensive consideration of joint optimization across multiple factors in a multi-UAV system, which increases its practical applicability, (2) the development of an effective iterative algorithm with proven convergence, and (3) the design of a low-complexity initialization scheme for UAV trajectory optimization.

It is found that the four papers are all associated with the fourth trend "efficient communication and trajectory optimization for intelligent UAV networks", and the consistent idea is to use UAV path planning as a way to shorten the communication distance, improve the flight safety and reduce the energy consumption. Since most of the application scenarios currently being considered for UAVs are in urban low-altitude environments., the constraints in UAV path planning are mainly the safety intervals between UAVs, including vertical, horizontal, and vertical safety intervals, hovering altitude, communication coverage, time constraints, and priority constraints [208,212], and the four papers are mainly aimed at optimizing these conditions.

In addition, it is worth noting the frequency of appearance of author Zeng Y. The data from WoS shows that Zeng Y has 161 publications from 2012 to 2024, citing 10,187 papers in total and being cited 18,231 times in WOSCC, which is a great contribution to the field of wireless communication. Figure 13 shows the author Zeng Y's 2012–2024 publications and citations distribution.

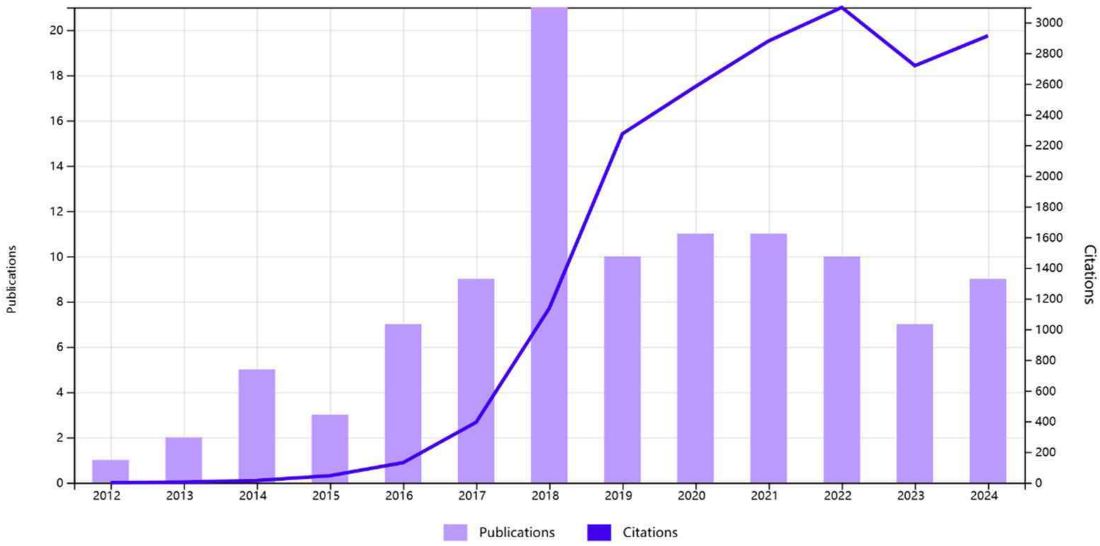


Figure 13. Author information of publications and citations from WoS, 2012–2024.

Other prominent authors who have made significant contributions to the field of UAV path planning, along with the year and corresponding number of their highest collaborative papers in parentheses (data from CiteSpace), include Rui Zhang (2017, 22), Dingcheng Yang (2019, 19), Nan Zhao (2019, 18), Wei Ni (2020, 18), Jie Chen (2017, 17), Hailong Huang (2020, 16), and Qingqing Wu (2019, 14).

6. Research Hot Spots and Frontier

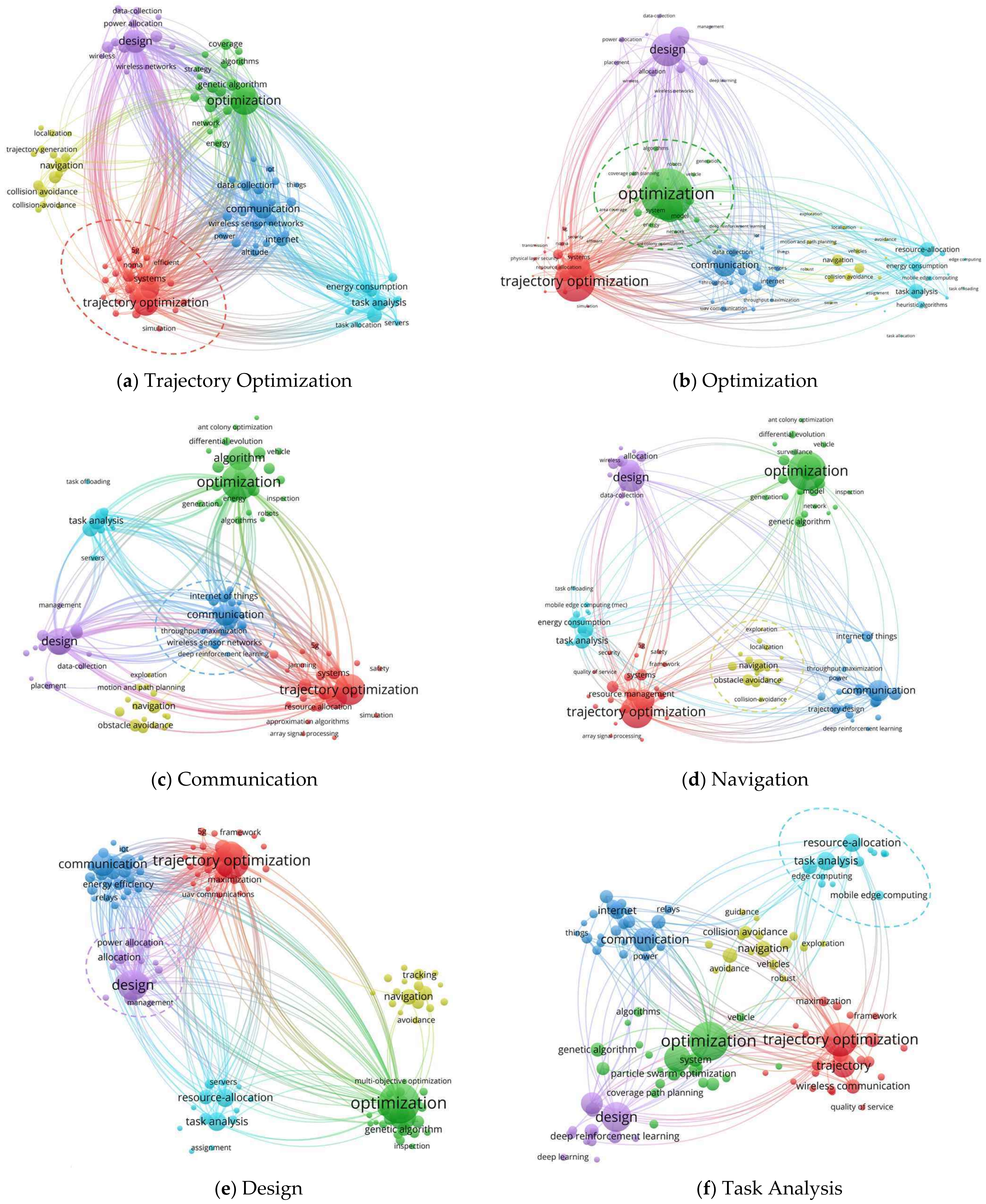
6.1. Keyword Clustering Analysis

VOSviewer's keyword co-occurrence cluster analysis is a valuable tool for identifying research hotspots and tracking the evolving focus within a specific field. In the context of UAV path planning, clustering analysis helps uncover how related keywords tend to co-occur, indicating areas of significant research activity. The basic principle behind this analysis is that keywords that frequently appear together in the literature are grouped, and the strength and direction of their association are measured to form clusters [213].

To perform this analysis, the plain text file containing the relevant publication data was imported into VOSviewer. This resulted in the generation of 8099 keywords, with a minimum occurrence threshold set at 25. As a result, 141 keywords met the criteria, while 118 keywords were filtered out. The network visualization option was then chosen to view the clustering results.

The analysis revealed six distinct clusters with a total of 3431 links and a total link strength value of 24,714. Figure 14 shows the UAV path planning keyword clustering network, with each cluster labeled by its most frequent keywords. These clusters include:

Trajectory Optimization;
Optimization;
Communication;
Navigation;
Design;
Task Analysis.



(a) Trajectory Optimization (b) Optimization

(c) Communication (d) Navigation

(e) Design (f) Task Analysis

Figure 14. Keyword clustering networks. Note: The size of the keywords and the size of the circles in the charts are directly proportional to the frequency of the keywords; keywords with the same research theme have the same color; the higher the centrality score of the circles, the greater the importance of the keywords in the research area. Clusters are visually distinguished by different colors, i.e., cluster a (red), cluster b (green), cluster c (blue), cluster d (yellow), cluster e (purple), and cluster f (cyan), and we include the clusters of the (**a**–**e**) diagrams with dashed ellipse boxes of the same color as the clusters.

The specific keyword information for each of these six clusters is detailed in Table 5.

Table 5. Internal information on keyword clusters in Figure 14.

Cluster	Size	Keywords (Occurrences)
a	24	trajectory optimization (514); resource management (133); energy consumption (123); systems (116); wireless communication (116); search (102); tracking (81); traveling salesman problem (62); route planning (59); coverage path planning (57); maximization (57); flight (49); NOMA (48); 5G (46); energy efficiency (39); physical layer security (39); avoidance (38); framework (36); UAV communications (34); security (34); batteries (30); safety (30); simulation (28);quality of service (25); efficient (25); transmission (25)
b	24	optimization (664); algorithm (334); genetic algorithm (110); system (110); particle swarm optimization (103); model (99); coverage (96); vehicles (65); differential evolution (65); algorithms (60); energy (59); altitude (57); vehicle dynamics (50); vehicle (48); generation (48); surveillance (45); robots (38); network (38); strategy (32); ant colony optimization (31); inspection (30); area coverage (27); costs (25); multi-objective optimization (25)
c	23	communication (277); networks (237); internet (138); internet of things (111); data collection (105); deep reinforcement learning (105); wireless sensor network (96); three-dimensional displays (74); throughput (71); sensors (68); performance (53); relays (49); throughput maximization (47); internet of things (IoT) (47); information (45); IoT (40); interference (36); jamming (30); sky (30); time (30); base stations (28); things (26); array signal processing (25)
d	17	navigation (139); obstacle avoidance (119); collision avoidance (89); deployment (65); motion and path planning (49); radar (46); localization (45); optimal control (36); robust (35); guidance (30); task assignment (29); exploration (27); model predictive control (27); approximation algorithms (27); motion (26); task allocation (25); mission planning (25)
e	14	design (408); allocation (111); trajectory design (97); power allocation (65); placement (59); challenges (56); data-collection (49); target tracking (47); power (45); wireless networks (38); deep learning (34); swarm (33); management (31); wireless (25)
f	14	task analysis (181); resource-allocation (175); heuristic algorithms (86); resource allocation (77); capacity (65); mobile edge computing (60); minimization (52); data models (43); servers (39); reconfigurable intelligent surface (37); edge (33); edge computing (30); assignment (28); task offloading (25)

Based on the cluster analysis results, we observe that clusters (a) Trajectory Optimization (514) and (b) Optimization (664) share significant similarities and are the most frequently occurring clusters. Cluster (f) Task Analysis (181), on the other hand, is a more specific subset of (b) Optimization, focusing on task-specific requirements, objectives, and constraints.

Keywords from clusters (a), (b), and (f) can be categorized into three broad categories: "Constraint", "Theoretical approach", and "Application".

- Constraint: This category includes factors that directly influence UAV path planning and must be taken into account in optimization. Relevant keywords include energy consumption (123), capacity (65), altitude (57), flight (49), physical layer security (39), network (38), time (30), safety (30), batteries (30), costs (25).
- Theoretical approach: These are the algorithms, models, and optimization methods used in UAV path planning. Notable keywords include genetic algorithm (110), particle swarm optimization (103), model (99), heuristic algorithms (86), differential evolution (65), traveling salesman problem (62), maximization (57), minimization (52), NOMA (48), ant colony optimization (31), simulation (28).
- Application: This category includes the practical implementation of UAV path planning in real-world scenarios, such as communication, task scheduling, and resource

management. Important keywords include resource management (133), systems (116), wireless communication (116), mobile edge computing (60), mobile computing (11), route planning (59), coverage path planning (57), vehicle (48), 5G (46), surveillance (45), reconfigurable intelligent surface (37), inspection (30), edge computing (30), assignment (28), task offloading (25), transmission (25).

Additionally, there are some emerging keywords that, while not meeting the threshold for frequency, represent growing trends in the field, such as deep reinforcement learning, convolutional neural networks, collaborative path planning, model predictive control, generative adversarial networks, simultaneous localization, and mapping (SLAM).

Clusters (c) Communication (277) and (d) Navigation (139) are two crucial components of UAV path planning, with significant interdependence. The navigation system provides the UAV's precise location and planned trajectory, while the communication system ensures that the UAV receives timely updates, shares status, and collaborates with other UAVs. This integration becomes especially critical in multi-UAV collaborations, remote control, and path planning within complex environments.

Core concepts associated with communication and navigation include networks (237), internet (138), throughput (71), sensors (68), deployment (65), performance (53), radar (46), information (45), localization (45), interference (36).

Several methods related to the optimization of communication and navigation systems in UAVs also stand out: data collection (105), deep reinforcement learning (105), three-dimensional displays (74), throughput maximization (47), array signal processing (25), model predictive control (27), approximation algorithms (27).

To further explore the frontiers of research keywords, we selected the No Normalization option in VOSviewer, which preserves the original characteristics of the data, ensuring that the network structure obtained reflects the inherent properties of the data. As a result, the analysis remains transparent and accurate.

By choosing the "Overlay Visualization" view with the time range set from 2020 to 2024, we generated the keyword time-zone network for this period, as illustrated in Figure 15, and detailed internal information is presented in Table 6.

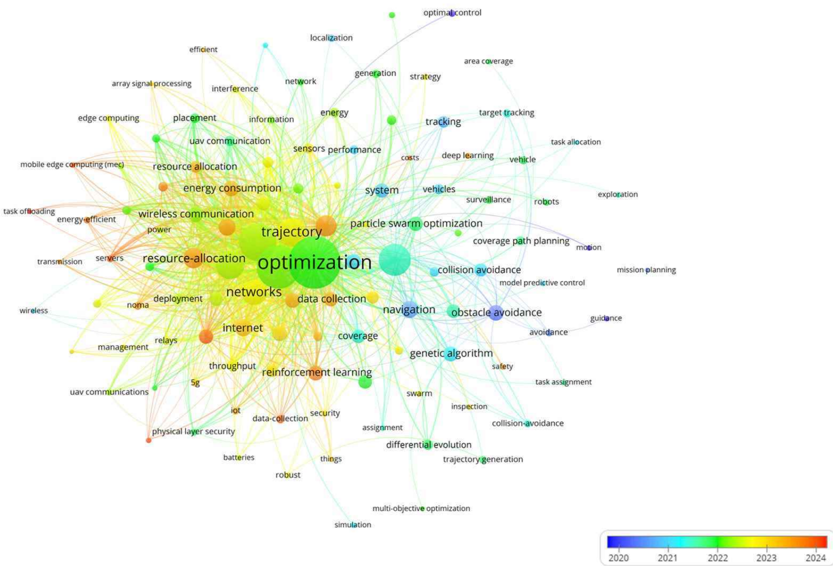


Figure 15. Keyword time zone network, 2020–2024. Note: The lines represent the connections between keywords, with the color indicating the year. The color gradient, from dark blue to dark red, corresponds to the years 2020 to 2024, from the earliest to the most recent. The size of the nodes reflects the total frequency of keyword appearances during the respective periods, with larger nodes indicating higher frequencies of keyword occurrences.

Table 6. Internal information on keywords in Figure 15.

Period	Keywords
2020–2021	obstacle avoidance; navigation; avoidance; guidance; mission planning; motion; tracking; optimal control; performance; localization; tracking
2021–2022	optimization; system; genetic algorithm; coverage; coverage path planning; collision; vehicles; collision-avoidance; trajectory generation; multi-objective optimization; differential evolution; model predictive control; surveillance; robots; exploration; area coverage; generation; simulation
2022–2023	particle swarm optimization; swarm; information; UAV communication; placement; interference; trajectory; throughput; 5G; security; robust; batteries; physical layer security; management; relays; energy; networks; wireless; wireless communication; power; deployment
2023–2024	deep learning; reinforcement learning; mobile edge computing (MEC); costs; data-collection; IoT; NOMA; servers; safety; transmission; energy-efficient; energy consumption; task offloading; things; inspection; resource-allocation; internet

We observe that the most prominent keywords since 2023 include deep learning, reinforcement learning, mobile edge computing (MEC), data collection, IoT, NOMA, and task offloading, among others. These keywords reflect the rapid advancements in artificial intelligence, communication technology, and computational architecture. Such progress has significantly enhanced the autonomous decision-making, real-time computational efficiency, and group collaboration capabilities of UAVs in complex dynamic environments. These trends are expected to remain pivotal in the future and warrant ongoing attention.

6.2. Frontier Applications

In addition to the research themes mentioned above, research on application scenarios is necessary. After reviewing 4416 papers, we found that UAV path planning applications can be broadly categorized into five key areas: Engineering optimization, Environmental monitoring, Rescue and emergency response, Wireless communications, and Logistics delivery.

- Engineering optimization in the context of UAVs focuses on enhancing the ability to perform various tasks, such as construction, bridge inspection, and transmission line monitoring. Path planning in these scenarios accounts for factors such as operational efficiency, flight safety, accuracy requirements, and the need for multi-task collaboration [214].
- Environmental monitoring primarily involves the collection of environmental data, particularly in areas such as climate change, air quality, pollution source tracking, and wildlife protection [215]. In this context, path planning accounts for factors like terrain, climate, and other variables to ensure comprehensive and accurate data collection.
- Rescue and emergency response operations heavily rely on efficient path planning, with UAVs deployed in hazardous environments to minimize casualties, improve rescue efforts, and support post-disaster recovery. Key applications include disaster area assessments, personnel search and rescue, and the evacuation of individuals from disaster zones [216].
- Wireless communications have become increasingly important with the rise of technologies such as the IoT and 5G. UAVs are widely employed to establish tempo-

rary communication networks, including communication relays, and data transmission [217]. Path planning enables UAVs to identify optimal flight paths for signal coverage, ensuring reliable communication in designated areas.

- Logistics delivery aims to enhance delivery efficiency, optimize flight routes, and minimize energy and time costs. Path planning in this domain considers factors such as geographic information, weather conditions, no-fly zones, and the need to ensure the safety and accuracy of deliveries, including courier services, medical deliveries, and emergency material distribution [218].

Each of these five application scenarios has distinct characteristics. Engineering optimization focuses on enhancing the efficiency and safety of engineering tasks, while environmental monitoring emphasizes data accuracy and comprehensive coverage. Rescue and emergency response prioritizes rapid intervention and efficient task execution in critical situations. Wireless communication is centered on optimizing network topology and ensuring real-time communication, whereas logistics and distribution demand efficient, precise, and flexible path planning. As UAV technology and algorithms continue to advance, research in these application scenarios will drive the development of path planning technologies toward greater intelligence, dynamism, and multifunctionality.

In conclusion, the characteristics of the research literature analyzed in this paper, based on topics and application scenarios, are summarized in Table 7. Specifically, rows R1 through R9 are dedicated to the field of Engineering optimization. Rows R10 through R14 focus on Environmental monitoring. R15 to R20 is allocated to Rescue and emergency response. Wireless communication is the theme for rows R21 through R26, and R28 to R32 is dedicated to Logistics delivery.

Table 7. Technique, problem/methodology characterizing various application scenarios of UAV path planning.

R	References	Technique	Problem/Methodology Characteristics	Application
1	[62] 2023	MARL + CTDE	MARL approach is scalable and real-time; Centralized training and decentralized execution (CTDE); Negative and positive reinforcement is employed in the reward function.	UAV cluster collaboration missions
2	[219] 2024	BACOHBA + HBAFOA	Three-dimensional inspection environment model; Multi-indicator hybrid cost function; Has better performance in terms of fast-solving ability, solution accuracy and optimization stability.	Inspection of transmission lines
3	[176] 2024	UAV-DPPA-DWA	Dynamic-based path; Algorithm combined with dynamic window approach; The novel elliptic tangent graph algorithm based on the evaluation of offset degree and obstacle distance; Various types of complex dynamic obstacle avoidance scenarios.	Obstacle avoidance
4	[220] 2022	DETACH + STEER	Large drone tasks are divided into smaller ones; Considering the maximum waypoint coverage; Offline path-planning algorithms detect possible in-flight collisions; DETACH and STEER perform vector intersection checks for flight path analysis.	Obstacle avoidance
5	[221] 2023	HGWODE	GWO and DE algorithms cooperate to balance exploitation and exploration; The position-updated equation of GWO to boost exploitation; A rank-based mutation strategy is implemented in DE algorithm to promote exploitation capacity.	Algorithmic improvements
6	[222] 2023	HISOS-SCPSO	Employing chaotic logistic mapping; Difference strategy; Novel attenuation functions; The population regeneration strategy; Cubic B-spline curve.	Algorithmic improvements

Table 7. *Cont.*

R	References	Technique	Problem/Methodology Characteristics	Application
7	[223] 2023	VPF-RRT* + DRNN-PI	Traditional planned paths are not smooth, the distance is long, and the fault tolerance rate of the planned path is low; Environmental disturbance and maintaining track along the planning path.	Navigation to reduce environmental interference
8	[224] 2023	BA + CNN + BOFBA	Cooperation of obstacle avoidance and target tracking; All perception information, including avoidance and tracking, was fused during the UAV motion decision phase; The Hawk-eye algorithm with LOS tracking rules.	Algorithmic improvements
9	[194] 2023	MILP + B&P + BLA + TS	Two-echelon network; A mixed integer linear programming model; Several constraints such as customers' delivery deadlines and drones' energy capacity; The exact labeling algorithm is utilized.	The two-level vehicle path problem
10	[134] 2023	DPC + LiDAR	Covering the creation of digital twins; Laser scanners as light emitters; Point clouds are aligned using georeferenced points measured with a total station; Dense point clouds from a laser scanner are used to generate meshes.	Identify architectural and archaeological heritage
11	[225] 2024	DLS + USS + IUS + AIS	The industrial source complex (ISC3) model; Determining sampling points (SPs) to collect data; Building the shortest path to visit chimneys; Visiting downwind (DW) SPs first and then flying down to pass upwind (UW) SPs.	Recognize chimneys with excessive exhaust emissions
12	[135] 2022	SfM + MVS	Based on the combination of SfM-MVS and UAV-generated images; Utilizing image acquisition technologies and 3D model-building software.	3D reconstruction
13	[226] 2022	SA + ABC	Given battery capacity constraints; Using a ship (such as a patrol ship) as a UAV mobile supply base; Overcoming battery limitations and increasing monitoring coverage; Solving joint routing and scheduling problems of ship-deployed multiple UAVs (SDMUs).	Vessel air pollution detection

Table 7. *Cont.*

R	References	Technique	Problem/Methodology Characteristics	Application
14	[193] 2023	GA	Heterogeneous UAVs applied to solving the issues of coverage; Multi heterogenic UAVs coverage path planning with moving ground platform (mhCPPmp); Allowing solving the task of covering fields of different shapes; Lower flight costs.	Precision agriculture
15	[227] 2023	DTU + TSI + RE	NP-hard problem; Integrated truck-UAV collaborative scheduling model; The time for making decisions is tight; Frequently threatened by the disruption of road networks and infrastructures.	Urban emergency response
16	[228] 2023	Dijkstra + SURF + RANSAC	Based on the needs of continuous road image capture and pavement disease recognition; Automatic route planning and control; Continuous photography control; Image stitching and smoothing tasks.	Road damage detection
17	[229] 2023	FTA + BN	Hybrid risk identification model; Fault tree structure of UAV-related public safety accidents; Given initial risk factors; The fault tree is converted into a BN; Diagnostic inference and sensitivity analysis are applied to identify key risk factors.	Risk identification
18	[230] 2023	SICq + RPA	Forming a communication relay chain between the target and the base station as fast as possible; Balancing detection and connection requirements; Utilizing joint optimization for the search drones and decoupled optimization for the relay drones.	Search and rescue missions
19	[231] 2023	APF-IRRT*	High computational efficiency; Adapted with adaptive step size; Adaptive search range; Giving the target directivity of the extended nodes.	Search and rescue missions
20	[232] 2023	RL	Limited amount of power at their disposal; UAV-based autonomous mine detection framework; Based on deep learning and then constructing the coverage route plan for the aerial survey; Multiple coverage path patterns are used to identify the ideal UAV route.	Intelligent landmine detection

Table 7. *Cont.*

R	References	Technique	Problem/Methodology Characteristics	Application
21	[140] 2024	MEC + SA + AGSP	Supporting cloud-like computing capabilities at the edge of the network; Offering low-latency services; Integrated cloud edge network with multiple mobile users (MUs) and layered drones; Static and dynamic applications supporting task offloading.	Cost-efficient task offloading
22	[233] 2022	SCA + BCD	Extremely high sensing resolution, large coverage area; No additional spectrum required; Minimizing propulsion energy and guaranteeing the required sensing resolutions on a series of interesting landmarks; Better energy efficiency.	Communication-assisted radar sensing
23	[234] 2023	DMSPSO + CLPSO	Cooperative path planning model; Given communication constraints and the impact of obstacles in the flight environment on the quality of communication.	Path planning with communication constraints
24	[235] 2024	PPO	Balancing mission objectives with the imperative to minimize radar exposure; Reducing the cognitive burden of air traffic controllers; Action-shaping mechanism; Operational viability in congested radar environments.	Realizing minimized radar observability
25	[236] 2022	DRL + QiER	Associated with the associated quantum bit (qubit); Minimization problem on the weighted sum of time cost and expected outage duration; UAV's adjustable mobility; Applying Grover iteration-based amplitude amplification technique.	Cellular-connected UAV network
26	[237] 2022	COS + AB-3DULA	Antenna array; Three-dimensional (3D) uniform linear array (ULA); Nonlinear EH model; Efficiency maximization problem; Complicated 3D ULA antenna pattern; Different beamforming preferences.	UAV-enabled wireless power transfer
27	[238] 2023	DRL + SAC	Multi-UAVs as mobile aerial ISAC platforms; Joint user association, UAV trajectory planning, and power allocation problem; Equivalent transformation of the optimization objective based on the symmetric group; Random and adaptive data augmentation schemes.	Resource allocation in UAV network

Table 7. *Cont.*

R	References	Technique	Problem/Methodology Characteristics	Application
28	[239] 2022	MILP + HGSA + UO-MinMin + MC-SA	Joint-optimization framework; GA employs a novel stochastic crossover operator to search for the optimal global position of customers; SA utilizes local search operators to avoid the local optima.	Routing and scheduling optimization
29	[240] 2023	Voronoi diagram + A* + DBSCAN	Constructing a city airspace grid model in which the characteristics of the airspace are mapped onto the grid map; Obstacle clustering algorithm; Based on DBSCAN to generate representative obstacle points as the Voronoi seed nodes.	Drone public route network planning
30	[241] 2022	Saturated FM2 + VCG	UTM models; Resolving path conflicts from different perspectives; Sequential delay (SD) model; Sequential delay/reroute (SDR) model; Full optimization (FO) model; Batch optimization (BO) model.	Traffic management and resource allocation in low-altitude logistics
31	[242] 2023	NLO	Centralized supply chain network optimization model; Maximizes the total profit; Including realistic features such as low battery capacities and short delivery ranges; The constrained nonlinear optimization problem is formulated as a variational inequality.	Last mile package delivery
32	[243] 2022	MILP + SA + VNS	A mixed integer linear programming model; Assignment of each customer location to a vehicle; Routing of truck and UAVs; Scheduling drone LARO and truck operator activities at each stop.	Last mile package delivery

7. Conclusions

This study employs bibliometric and visualization tools, including CiteSpace, VOSviewer, and the Bibliometrix R package, to analyze the field of UAV path planning. A dataset comprising 4416 publications was extracted from the WOSCC. An initial retrospective analysis identified four distinct developmental stages and foundational models within the discipline: the early exploratory stage, the classical algorithm stage, the intelligent algorithm application stage, and the multi-intelligence collaborative stage. This framework facilitates the systematic organization of the knowledge network for both re-searchers and practitioners. Subsequently, a quantitative analysis was conducted, revealing a significant increase in the number of publications and citations related to UAV path planning from 2000 to 2024, particularly after 2018. This surge is likely linked to advancements in artificial intelligence, machine learning, 5G, and Internet of Things (IoT) technologies, as well as market and policy influences and a growing demand for practical applications. These developments have positioned UAVs as a prominent subject of academic inquiry. Since 2013, several UAV-focused journals have been established, with “Drones” and the “IEEE Internet of Things Journal” making notable contributions to the scientific literature in this area. At the national and regional levels, China and the United States have emerged as the leading contributors to UAV path planning research, each fostering core institutions that generate substantial research output.

Through the application of co-citation clustering analysis, we have identified four prominent research trends within this domain: “multi-objective cooperative control problems in cluttered natural environments”, “high performance UAV obstacle avoidance technology”, “intelligent path planning and scene reconstruction in urban environments”, and “efficient communication and trajectory optimization for UAV networks”. These trends represent the forefront of technological advancements in the UAV sector, encompassing aspects such as multi-agent collaboration, intelligent obstacle avoidance, urban applications, and optimization challenges. They highlight the research imperatives associated with autonomous flight, collaborative operations, and interactions between UAVs and ground-based systems in complex environments. Additionally, we provide a selection of significant papers for reference and further investigation.

In the research hotspot analysis, six main clusters were identified through keyword clustering: trajectory optimization, optimization, communication, navigation, design, and task analysis. The keyword time-zone map for 2022–2024 further revealed several recent focal points of research, including deep learning, reinforcement learning, MEC, data collection, IoT, NOMA, and task offloading. These keywords help identify various research directions and subfields within UAV path planning, highlighting the structural characteristics of the field. In terms of application scenarios, the primary areas include engineering optimization, environmental monitoring, rescue and emergency response, wireless communications, and logistics delivery. The analysis of these papers provides valuable insights that can assist researchers in understanding the knowledge structure and future development directions within the field.

However, it is important to acknowledge several limitations in our study. The first limitation concerns the restricted data resources. In this paper, all the data were obtained from a single database, WOSCC, and it is challenging to ensure that all relevant literature on UAV path planning is encompassed within this dataset. This limitation is particularly pertinent with regard to non-English literature and studies outside the scope of the search criteria. Second, the results generated by CiteSpace and VOSviewer software may be influenced by algorithmic noise and sampling bias. As a result, different software tools may yield varying results when analyzing the same dataset, potentially leading to discrepancies in the findings. Finally, in bibliometric analysis, the interpretation of results derived from software tools involves an inherent degree of subjectivity, especially when evaluating the internal characteristics of a research field. Although we endeavored to ensure comprehensiveness and accuracy—such as by excluding publications with low relevance, employing synonyms to broaden the search, and cross-referencing to reduce errors—our analysis may still be subject to bias or fall short in fully capturing the deeper aspects of the field. Further research will require a more nuanced approach to gain deeper insights.

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Abbreviations

The following abbreviations are sequentially used in this paper:

BACOHBA	Bidirectional ant colony and discrete honey badger algorithm
HBAFOA	Honey badger-fruit fly algorithm
DETACH	Detect and Remove path intersections to avoid collisions and hazards
HGWODE	Hybrid GWO and differential evolution algorithm
BA	Bat algorithm
BOFBA	Bio-inspired optical flow balance algorithm
B&P	Branch-and-price
BLA	Bidirectional labeling algorithm
TS	Tabu search
LiDAR	Light detection and ranging
DPC	Dense point clouds
DLS	Dual-location sampling scheme
USS	Upward spiral sampling scheme
IUS	Inverted-U sampling scheme
AIS	Asynchronous isometric sampling scheme
SfM	Structure from motion algorithm
MVS	Multi-view stereo algorithm
SA	Simulated annealing algorithm
ABC	Artificial bee colony algorithm
DTU	Dynamic truck-UAV collaboration strategy
TSI	Tabu search-based integrated scheduling algorithm
RE	Recursion-based evaluation algorithm
RANSAC	Random sampling consistency algorithm
SURF	Speeded-up robust features algorithm

FTA	Fault tree analysis
BN	Bayesian network
SICq	Simultaneous inform and connect with QoS
RPA	Dynamic relay positioning algorithm
AGSP	Based particle swarm optimization
SCA	Successive convex approximation
BCD	Block coordinate descent
DMSPSO	Dynamic multi-swarm PSO algorithm
CLPSO	Comprehensive learning PSO algorithm
QiER	Quantum-inspired experience replay
COS	Cosine-based approximation
SAC	Soft actor-critic algorithm
HGSA	Hybrid genetic and simulated annealing
MC-SA	Monte Carlo simulation-based sensitivity analysis
DBSCAN	Density-based spatial clustering of applications with noise
VCG	Vickrey-clarke-groves mechanism
NLO	Nonlinear optimization
VPF-RRT*	Virtual potential field RRT*
DRNN-PI	Deep recurrent neural networks PI
APF-IRRT*	Artificial potential field -improved rapidly exploring random trees
ISOS	Improved symbiotic organisms search
SCPSO	Sine–cosine particle swarm optimization
PPO	Proximal policy optimization algorithm

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