REVIEW ARTICLE

Toward Low-Carbon Aerial Intelligence: A Comprehensive Review of Evolution, Applications, and Future Trends

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Abstract

Achieving carbon neutrality in the aviation sector demands transformative technologies, and Artificial Intelligence (AI)-enabled aerial unmanned systems are emerging as a critical enabler of low-carbon flight operations, environmental monitoring, and sustainable airspace governance, yet a comprehensive synthesis that jointly addresses their technical architecture, climate-oriented applications, and regulatory pathways remains limited. This review provides a systematic analysis of AI-enabled aerial unmanned systems using a structured literature review framework aligned with PRISMA principles. We first summarize the evolution and classification of aerial unmanned platforms, then propose a layered technical perspective covering perception, decision-making, control, collaboration, and support capabilities. On this basis, we map representative advances in military and civilian scenarios, including autonomous navigation, multi-UAV cooperation, infrastructure inspection, emergency response, and logistics operations. A dedicated discussion further examines AI-driven decarbonization pathways, showing how intelligent energy management and trajectory optimization, together with UAV-based environmental sensing, can contribute to low-carbon aviation and climate-oriented operations. We also identify major barriers to large-scale deployment, including robustness in complex environments, edge intelligence constraints, explainability and trust, cybersecurity, regulatory compliance, and interdisciplinary talent gaps. Finally, we outline future directions centered on embodied intelligence, stronger onboard computing, swarm-level autonomy, and internationally harmonized standards. This review offers an integrated roadmap for researchers, engineers, and policymakers to advance safe, scalable, and sustainable AI-enabled unmanned aviation.

Keywords: aerial unmanned systems, unmanned

Submitted: 07 April 2026
Revised: 22 June 2026
Accepted: 20 August 2026
Published: 22 September 2026

Vol. 1, **No.** 2, 2026.
10.62762/JCN.2026.328644

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Citation
Liu, Z., Wang, Y., & Yim, P. (2026). Toward Low-Carbon Aerial Intelligence: A Comprehensive Review of Evolution, Applications, and Future Trends. *Journal of Carbon Neutrality*, 1(2), 127–154.

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aerial vehicle (UAV), artificial intelligence (AI), carbon neutrality, low-carbon aviation, green aviation, sustainable development, development trends, swarm intelligence.

1 Introduction

Achieving global carbon neutrality requires fundamental transformations across all sectors of human activity, including aviation. Aerial unmanned systems, widely known as Unmanned Aerial Vehicles (UAVs), have evolved beyond simple remotely piloted devices into sophisticated systems integrated with advanced sensors and controllers. The integration of Artificial Intelligence (AI) has catalyzed a paradigm shift in this domain, endowing these systems with autonomous capabilities such as complex environment perception, intelligent decision-making, and cooperative control—capabilities that directly underpin low-carbon flight operations, precision environmental monitoring, and AI-driven decarbonization pathways. This convergence represents a new frontier in aerospace technology, fundamentally transforming flight operations from traditional execution to intelligent autonomy. By enhancing flight safety and optimizing air traffic management, intelligent UAVs are rapidly expanding their footprint globally, playing pivotal roles in high-stakes missions ranging from logistics to emergency response in remote areas.

Recognizing the strategic imperative of intelligent unmanned systems, major global powers have expedited their development agendas to secure a competitive edge. In August 2018, the US Department of Defense released the Integrated Roadmap for Unmanned Systems (Fiscal Years 2017-2042), prioritizing key technologies including autonomy, machine learning, and human-machine collaboration [1]. Similarly, the Russian government approved the Strategy for the Development of Unmanned Aerial Vehicles by 2030 in June 2023, aiming to foster a high-tech economic sector and bolster infrastructure for safe Unmanned Aircraft Systems (UAS) operations [2]. More recently, in March 2024, four Chinese ministries jointly issued the Implementation Plan for the Innovative Application of General Aviation Equipment (2024-2030). This plan delineates a roadmap for a high-end, intelligent, and green general aviation industry, envisioning the ubiquitous integration of unmanned equipment into agriculture, logistics, and urban governance [3].

The evolution of UAVs is further accelerated by the synergy of emerging technologies such as Big Data, 5G communications, and Edge Computing [4–8]. These advancements have significantly elevated the intelligence level of UAVs, enabling robust connectivity and real-time data processing in diverse scenarios. Driven by these innovations, the global UAV market is projected to exceed 48 billion dollars by 2029 [9, 10], underscoring the immense growth potential in infrastructure, agriculture, and transportation. The development of UAV technologies is transforming the traditional flight operation mode, while reshaping the human-machine interaction mode for future flight and the architecture of air traffic management (ATM) [11–13]. In addition, the evolution of UAV technologies has promoted the update of airworthiness standards and the transformation of airspace management [14–16]. As these transformations deepen, regulations and policies related to UAV safety, privacy and supervision are being continuously updated to adapt to the challenges and opportunities brought by emerging technologies [17–19].

Central to this transformation is the application of AI, which has revolutionized automatic control by advancing it toward systematization and modernization. AI algorithms empower UAVs with adaptive capacities for automatic obstacle avoidance, dynamic path planning, and autonomous decision-making in complex environments, thereby optimizing resource allocation and operational quality [20]. These advances have promoted the systematic, standardized, and increasingly intelligent development of autonomous control technologies, bringing revolutionary changes to various industries [21]. Furthermore, against the backdrop of global carbon neutrality goals, the integration of AI and UAVs emerges as a critical enabler for sustainable development. AI-driven flight control can greatly reduce energy consumption through trajectory optimization, while electric UAVs replace carbon-intensive traditional operations. This combination supports precision agriculture and environmental monitoring, fostering a multi-dimensional low-carbon ecosystem that aligns technological innovation with ecological security.

Despite the promising prospects, the widespread deployment of intelligent aerial unmanned systems faces challenges related to safety, regulation, and technological maturity. Consequently, a comprehensive review of the state-of-the-art is essential. This paper aims to provide a systematic overview of the development, classification, and application domains of aerial unmanned equipment.

Specifically, it explores the current status and trends of AI technologies within these systems, analyzes the transformative impact on the aerospace sector, and discusses the critical challenges and opportunities that lie ahead.

Research questions. To provide a clear problem-driven focus, this review is organized around three central research questions that unify all sections:

1. **RQ1**: How does AI enable autonomy in aerial unmanned systems across the perception, decision-making, control, collaboration, and support layers?
2. **RQ2**: How are general-purpose AI methods adapted to UAV-specific constraints (limited onboard computing, energy budget, real-time control, and complex operating environments), and what are the resulting accuracy–latency–robustness trade-offs?
3. **RQ3**: What are the main barriers (technical, regulatory, ethical, environmental) to the large-scale and climate-aware deployment of AI-enabled UAVs, and which research directions are most likely to overcome them?

All subsequent sections are structured to consistently support these three questions: Section 4 addresses RQ1 and RQ2 from a technological standpoint, Section 5 grounds them in real-world use cases including AI-driven decarbonization, while Sections 6 and 7 synthesize the answers to RQ3.

Contributions and positioning with respect to existing surveys. Several recent works have surveyed AI for UAVs or AI for aerospace engineering. In particular, the comprehensive survey by Sai et al. [22] provides a broad taxonomy of AI techniques for UAV-related tasks (computer vision, communication, security, motion planning), while the systematic quantitative literature review by Hassan et al. [23] maps AI applications across the wider aerospace engineering domain (manned aviation, aircraft design, maintenance, MRO). Both references are excellent points of entry for the field. However, neither (a) explicitly addresses how AI components interact as a system across the perception–decision–control–collaboration–support stack within a UAV, (b) treats decarbonization and climate-oriented operations as a first-class topic, (c) integrates governance, certification, and explainability into a single roadmap, nor (d) covers the very recent shift towards embodied large multimodal models and vision–language–action policies onboard UAVs (post-2024 literature).

The present review complements these prior surveys with four distinctive contributions:

1. A PRISMA-2020-aligned SLR protocol (Section 2) with explicit search strings, eligibility criteria, and a quantitative summary of the retained corpus, ensuring transparency and reproducibility.
2. A unified layered technical framework (perception, decision-making, control, collaboration, support) coupled with a system-level perspective that explicitly discusses error propagation, real-time interaction, and integration challenges between layers (Section 4).
3. A dedicated treatment of AI-driven decarbonization pathways for aerial unmanned systems—covering eco-efficient platform design, AI-based energy management, climate-aware trajectory planning, and UAV-based carbon-sink and emissions monitoring (Section 5)—a dimension largely absent from existing AI/UAV surveys.
4. A forward-looking analysis of embodied intelligence, edge AI, and international standardization that connects technical maturity with regulatory and societal adoption (Sections 6 and 7).

Together, these elements position this review as an integrated technical–operational–regulatory roadmap rather than a purely algorithmic catalogue.

The remainder of this paper is organized as follows: Section 2 presents the methodological framework of this review, including search strategy, screening workflow, and synthesis criteria. Section 3 provides a comprehensive overview of aerial unmanned systems, delineating their historical evolution and classification standards. Section 4 dissects the core technical framework of AI-enabled UAVs. Section 5 bridges theory and practice by presenting applications in both military and civilian domains, with an additional focus on AI-enabled decarbonization pathways. Section 6 discusses the development trends of AI-driven aerial unmanned systems. Section 7 critically analyzes the multidimensional challenges inherent in integrating AI with UAVs. Finally, Section 8 concludes the paper and offers perspectives on future development of AI-driven UAVs.

2 Methodology: Systematic Literature Review Framework

This study adopts a Systematic Literature Review (SLR) methodology to ensure methodological rigor, transparency, and reproducibility in the synthesis of research on artificial intelligence in aerial unmanned systems. Unlike narrative reviews that are vulnerable to selective reporting, a systematic review follows a predefined protocol for identification, screening, eligibility assessment, and final inclusion. This process reduces selection bias and strengthens the reliability of synthesized conclusions. The methodological foundation of this review is grounded in established SLR guidelines [24, 25] and follows the PRISMA 2020 framework [26, 27], which has become a widely recognized standard for reporting systematic reviews across disciplines, including engineering and computer science.

The literature search was conducted across major databases, including IEEE Xplore, Scopus, Web of Science, and ScienceDirect. Search strings combined terms for artificial intelligence (e.g., machine learning, deep learning, reinforcement learning, graph neural networks), aerial unmanned systems (e.g., UAV, drone, aerial robot), and representative application domains such as navigation, inspection, agriculture, logistics, energy, and environmental sustainability. Boolean operators were used to balance coverage and precision. The time window was restricted to 2015–2026 to capture the rapid evolution of AI-enabled UAV technologies in the deep-learning era. For the technical synthesis, peer-reviewed journal papers and high-impact conference publications were prioritized; a limited number of authoritative policy, roadmap, market, and official project documents was retained only where needed for regulatory context, trend interpretation, or public case descriptions.

Study selection followed the PRISMA workflow: identification, screening, eligibility, and inclusion. After duplicate removal, titles and abstracts were screened for thematic relevance. Publications were retained if they explicitly addressed AI methods for aerial unmanned systems and reported technical, algorithmic, or experimental contributions with quantitative evidence. Studies focusing exclusively on non-aerial robotic systems, lacking explicit AI methodology, or offering purely conceptual discussion were excluded. The remaining papers underwent full-text review to confirm methodological soundness and relevance to the technical taxonomy in Section 4.

For each eligible study, structured data extraction was performed to capture AI techniques, application scenarios, data characteristics, evaluation metrics, and computational constraints. Particular attention was paid to the distinction between onboard intelligence and edge/cloud-assisted architectures, as well as to trends in model complexity, autonomy level, and system integration. Because evaluation protocols and mission settings are highly heterogeneous across studies, this review does not conduct a statistical meta-analysis; instead, it provides a qualitative synthesis and taxonomy-driven analysis.

2.1 Quantitative Summary of the Retained Corpus

After applying the PRISMA workflow described above, the final corpus retained for synthesis comprises peer-reviewed journal articles and high-impact conference papers, complemented by a limited set of authoritative policy and roadmap documents that are essential to the regulatory discussion. A descriptive overview of the corpus is provided in Table 1 (distribution by topical category) and Table 2 (distribution by publication year), and forms the empirical basis for the technical taxonomy developed in Section 4. References added solely for figure-source attribution, image licensing, or access information are cited in the captions and reference list but are not included in the SLR corpus statistics.

Three trends emerge clearly from this descriptive analysis. First, more than 66% of the retained literature was published in 2023–2026, confirming the very rapid acceleration of AI-enabled UAV research over the past three years and the timeliness of an updated review. Second, the technical layers (perception, decision-making, control, collaboration, support) jointly account for about 41% of the corpus, reflecting the historical algorithmic core of the field. Third, regulation/standards/ethics/certification together with AI-safety and decarbonization references represent more than one quarter of the corpus (28.6%); this larger share is a deliberate consequence of the review's positioning as an integrated technical–operational–regulatory roadmap rather than a purely algorithmic catalogue, and motivates the dedicated treatment of these topics in Sections 5 to 7.

3 Overview of Aerial Unmanned Systems

Aerial unmanned systems represent an integrated architecture encompassing UAVs, ground control stations, communication links, and mission payloads.

Table 1. Distribution of the retained SLR corpus ($N = 133$) by topical category. Categories aggregate technical layers, application domains, and thematic axes; counts are obtained by classifying each retained corpus entry along its primary contribution. Attribution-only figure sources and licensing references are excluded from this count.

Topical category	Count	Share
Perception (CV, multi-sensor fusion, NLP/semantic)	10	7.5%
Decision-making (RL, planning, embodied agents, predictive maintenance)	9	6.8%
Control & autonomous flight (adaptive, edge-AI)	14	10.5%
Collaboration & swarm intelligence (MUM-T, multi-UAV)	10	7.5%
Support layer (cybersecurity, energy, simulation, 5G/edge)	12	9.0%
Applications (military and civilian)	12	9.0%
AI-driven decarbonization & sustainability	12	9.0%
Regulation, standards, ethics & certification	21	15.8%
AI safety, safe RL & robustness	5	3.8%
Foundational AI surveys & evolution background	12	9.0%
Policy / industry / market roadmaps	12	9.0%
Methodology (SLR / PRISMA)	4	3.0%
Total	**133**	**100.0%**

Table 2. Temporal distribution of the retained SLR corpus ($N = 133$). Years are extracted from retained corpus entries; pre-2015 references are kept when they are foundational (PRISMA/SLR methodology, AI history, policy precedents). Attribution-only figure sources and licensing references are excluded from this count.

Period	Count	Share
Pre-2015 (foundational works, policy precedents)	6	4.5%
2015–2019 (deep learning consolidation)	15	11.3%
2020–2022 (RL, swarm, edge intelligence)	24	18.0%
2023–2024 (multi-modal, LLM/LMM, eVTOL)	43	32.3%
2025–2026 (embodied AI, climate-aware UAVs)	45	33.8%
Total	**133**	**100.0%**

Their evolutionary process is deeply intertwined with the advancement of electronics, materials science, and control technologies. Their development can be broadly divided into three stages: military origins, technological maturation, and civilian expansion. Correspondingly, UAVs can now be classified along multiple dimensions, including platform configuration, mission type, scale, altitude, and operational range.

3.1 Development History

The technical origins of aerial unmanned systems can be traced back to the early 20th century. The reconnaissance UAV developed by the United States Navy in 1917 for countering German submarines is widely regarded as one of the first unmanned aerial systems with tangible practical application value. During the interwar period between the two World Wars, UAV technology underwent rapid advancement and was extensively deployed in military missions including reconnaissance and target drone operations. In the Cold War era, bolstered by the maturity of electronic and control technologies, UAVs realized advanced military functionalities such as complex reconnaissance and precision strike, leading to the progressive sophistication of their technical systems.

Since the dawn of the 21st century, breakthroughs in Micro-Electro-Mechanical Systems (MEMS), lithium batteries, artificial intelligence and other core technologies have driven the developmental trends of miniaturization, cost-effectiveness, and increasing intelligence of UAVs. Their application scenarios have been comprehensively expanded from the military domain to the civil sector, with practical implementation gradually achieved in fields including agricultural plant protection, logistics distribution, environmental monitoring, and infrastructure inspection. A developmental pattern has thus been formed featuring the civilian transformation of military technologies and the reciprocal empowerment of military applications by civil technologies.

3.2 Classification of UAV Systems

Depending on distinct application requirements and technical attributes, aerial unmanned systems can be categorized through a variety of classification schemes. These complementary classification dimensions jointly cover a wide spectrum of application scenarios and operational demands.

1. **Classification by flight platform configuration**: Including fixed-wing UAVs, multi-rotor UAVs, unmanned airships, parawing UAVs, flapping-wing UAVs, etc. Fixed-wing UAVs feature long endurance

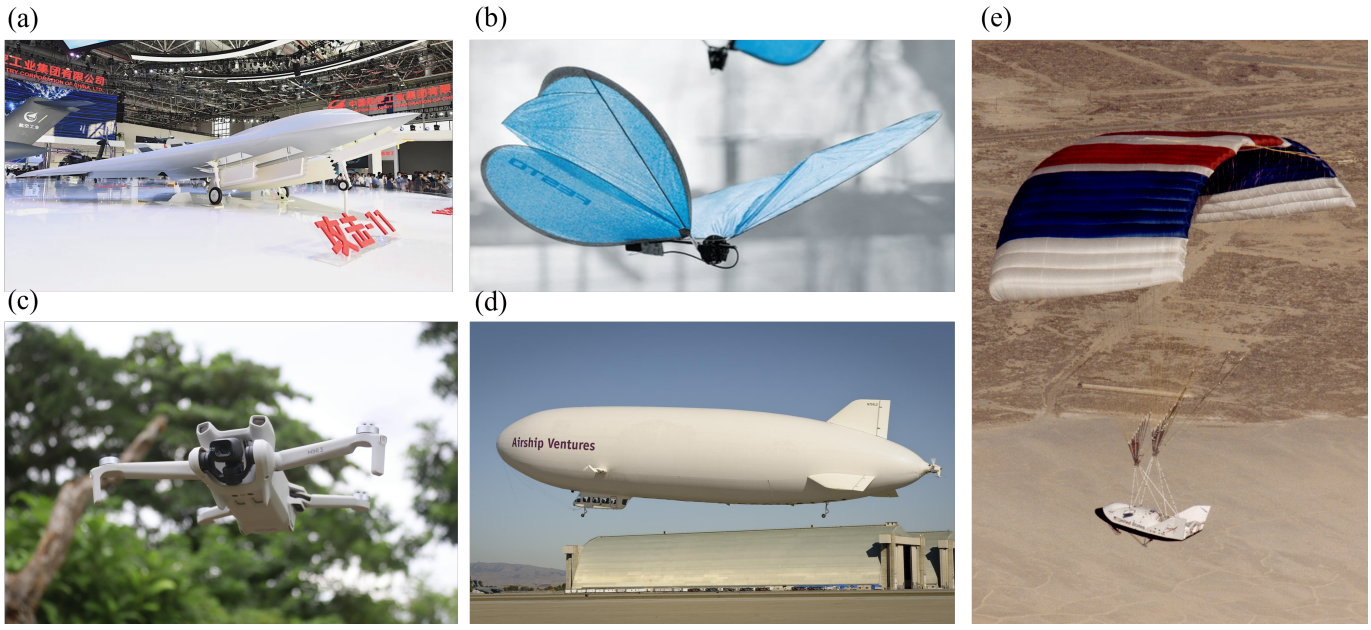


Figure 1. Classification of aerial unmanned equipment. (a) China's Attack-11 / GJ-11 unmanned combat aerial vehicle, source: Wikimedia Commons [28]; (b) Festo eMotionButterflies / bionic butterfly, source: Festo Bionic Learning Network [29]; (c) DJI Mavic 2, source: DJI official product information page [30]; (d) Airship Ventures' airship, source: NASA Images [31]; (e) NASA X-38 parafoil/parawing vehicle, source: NASA Images [32].

and high flight efficiency; multi-rotor UAVs are easy to operate and capable of vertical take-off and landing (VTOL); unmanned airships excel at long-duration loitering for surveillance missions (Figure 1).

2. **Classification by application and function**: Divided into military UAVs and civil UAVs. Military UAVs cover reconnaissance, decoy, electronic countermeasures, communication relay, unmanned combat aerial vehicles (UCAVs) and other types; civil UAVs are widely used in inspection, agriculture, meteorology, exploration, surveying and mapping and other fields (Figure 2).

3. **Classification by scale**: Based on performance indicators such as weight, flight altitude and flight speed, UAVs are classified into micro UAVs, light UAVs, small UAVs, medium UAVs and large UAVs. This classification serves as a fundamental basis for UAV airspace management and regulatory approval.

4. **Classification by operational radius and flight altitude**: By flight altitude, UAVs are categorized into ultra-low altitude, low altitude, medium altitude, high altitude and ultra-high altitude UAVs; by operational radius, they are divided into ultra-short range, short range, medium-short range, medium range and long range UAVs.

3.3 The Evolution of AI-Driven Unmanned Systems

Artificial Intelligence (AI) broadly refers to computational systems designed to simulate, comprehend, and execute functions characteristic of human intelligence [37]. While the conceptual origins of AI trace back to the 1950s, the 21st century has witnessed a paradigm shift driven by the exponential growth of computing power and data proliferation. These advancements have precipitated the extensive integration of AI into aerial unmanned equipment, catalyzing a fundamental transition toward autonomous, intelligent, and network-centric operations [22, 23].

Intelligent unmanned systems represent the culmination of rapid interdisciplinary convergence [61]. By leveraging massive datasets and synthesizing breakthroughs across diverse technological domains, these systems are engineered to possess advanced capabilities in comprehensive task execution, dynamic planning, decision-making, and logical reasoning. Unlike traditional automated machinery, these intelligent systems can independently undertake complex missions with minimal or no human intervention [62–64].

The evolutionary trajectory of unmanned systems can be categorized into three distinct stages: *program-based systems*, *adaptive automated systems*, and *autonomous intelligent systems*. The first stage is characterized

Table 3. Comparative analysis of representative AI algorithm families used in UAV systems, across the perception, decision-making, control, and collaboration layers.

Layer	Method family	Strengths	Limitations / trade-offs	Preferred scenarios
Perception	CNN-based detectors (YOLO, Faster R-CNN) [38, 39]	High accuracy on aerial imagery, mature toolchain, real-time on edge GPUs	Limited long-range context; degrades under occlusion / motion blur / domain shift [40]	Inspection, agriculture, surveillance
	Vision Transformers / DETR variants [38, 41]	Better global context, end-to-end detection, strong on small objects	Higher FLOPs and memory; harder onboard deployment without quantization	High-altitude SAR, small-object detection
	Multi-sensor fusion (Bayesian, Kalman, learned fusion) [42, 43]	Robustness under sensor failure / GPS denial, improved localization	Fusion latency; model complexity grows with sensor count	GPS-denied flight, low-visibility
Decision-making	Classical / model-based planners (A*, RRT*, MPC)	Predictable, certifiable, low compute	Poor scalability in unknown / dynamic settings	Constrained corridors, low-altitude logistics
	Deep RL (DQN, PPO, SAC, TD3) [44, 45]	Adaptive, learns end-to-end policies, strong in dynamic obstacles	Sample inefficient, sim-to-real gap, weak safety guarantees [46, 47]	Drone racing, swarm coordination
	Hybrid RL + planning / hierarchical RL / safety-constrained RL [48–51]	Combines safety of planners with adaptivity of RL; partial explainability; explicit constraint handling	More complex training pipeline; tuning effort	Mission-critical autonomy
Control	PID / robust / adaptive control	Mature, low compute, certifiable	Limited under aggressive maneuvers and high uncertainty	Routine flight
	Neural / fuzzy adaptive control [52, 53]	Handles strong non-linearities, gust / payload variations, high agility	Stability proofs hard; data-hungry	Acrobatic flight, wind
	Edge-AI lightweight models (pruning, quantization, distillation) [54]	Real-time inference on MCU/SoC, low energy budget	Accuracy degradation; calibration sensitivity	Onboard control loops
Collaboration	Swarm intelligence (PSO, ACO, bio-inspired) [55]	Decentralized, scalable, fault-tolerant	Limited theoretical convergence in dynamic missions	Large-scale swarms, area coverage
	Multi-agent DRL (MADDPG, QMIX, MAPPO) [56, 57]	Learned cooperation, climate-aware planning	Communication-heavy; non-stationary training	Cooperative interception, climate-optimal routing
	LMM / VLA-based agents [58–60]	Natural-language tasking, multi-modal grounding, generalization to new missions	High latency / energy; requires offboard or quantized inference	Mission generation, MUM-T

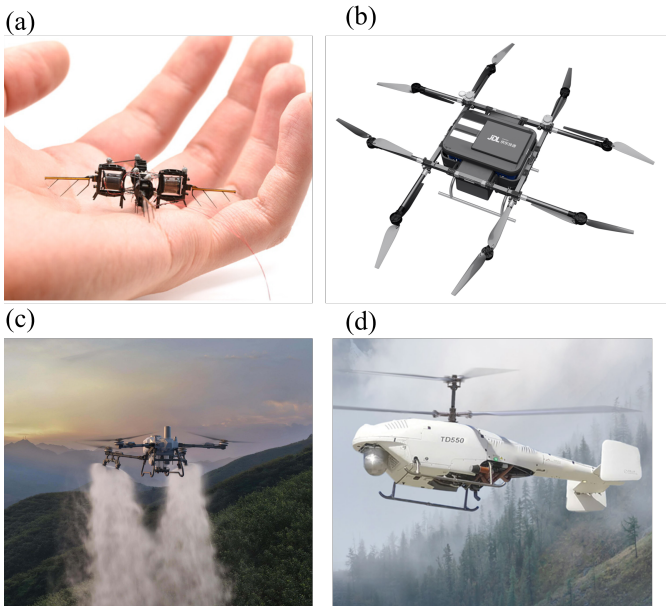


Figure 2. Different application fields of UAVs. (a) A micro-aerial robot developed by Massachusetts Institute of Technology (MIT). Reproduced from Ref. [33]; (b) the JDX-50 logistics drone developed by JD.com, Inc., source: JD Logistics product webpage [34]; (c) the AGRAS T100S agricultural drone developed by SZ DJI Technology Co., Ltd. (DJI), source: DJI Agriculture product webpage [35]; (d) the TD550 heavy-lift coaxial-rotor unmanned helicopter developed by Shenzhen United Aircraft Technology Co., Ltd. (United Aircraft), source: United Aircraft product webpage [36].

by deterministic operations, where systems function strictly according to pre-set programs and lack the capacity to adapt to environmental variability [65]. The second stage represents a significant leap in capability; these systems are endowed with perception, decision-making, and control modules, enabling adaptive adjustments in response to external changes [66, 67]. The final stage—autonomous intelligence—marks the pinnacle of this evolution. At this level, unmanned systems exhibit high-level cognitive autonomy, matching or even surpassing human performance in complex tasks [68, 69].

Looking forward, the aviation industry sector is poised to prioritize the development of these autonomous technologies. This strategic shift is essential for addressing the challenges of increasingly complex real-world environments and driving the high-quality, sustainable advancement of the aviation industry.

4 The Core Technical Framework of AI-Enabled Unmanned Aerial Systems

AI technology acts as the core driving force for the upgrading of aerial unmanned systems from automation toward autonomy and intelligence. The technical system that empowers aerial unmanned systems with AI follows a hierarchical architecture consisting of perception, decision-making, control, collaboration, and support, as shown in Figure 3. Technologies at each level are mutually reinforcing, collectively endowing aerial unmanned systems with autonomous operational capabilities. Meanwhile, to realize practical engineering deployment, AI algorithms must be modified for lightweight operation and adaptive performance by taking into account the inherent characteristics of unmanned aerial vehicles, such as limited onboard computing power, energy sensitivity, and complex operating environments.

To make the key technical trade-offs among accuracy, robustness, computational cost, and onboard deployability explicit, Table 3 provides a synthetic comparison of the main AI algorithm families employed at each layer. This comparison underpins the per-layer discussion that follows: rather than enumerating algorithms in isolation, the review highlights why specific methods are preferred in specific UAV scenarios, and how the dominant trade-off shifts as one moves from offline mission planning to real-time embedded control.

The comparison highlights two cross-cutting messages. First, no single algorithm family dominates: each layer exhibits a Pareto front between accuracy/robustness and computational cost/deployability, and the optimal choice depends on the mission profile. Second, recent trends—vision transformers, deep multi-agent RL, and embodied LMM/VLA agents—consistently push performance upwards, but at the cost of increased compute and energy requirements that are non-trivial to satisfy onboard, motivating the edge-AI techniques discussed in Section 7.

4.1 Perception Layer Technology: Accurate Perception of Environment and Targets

The perception layer serves as the "eyes and ears" of aerial unmanned systems, with its core objective being to achieve environmental perception, target recognition and tracking in complex environments, thereby providing data support for subsequent decision-making and control. The core AI technologies include:

1. **Computer Vision**: Leveraging models such as Convolutional Neural Networks (CNNs) and Transformers, it enables target detection, recognition and tracking in UAV

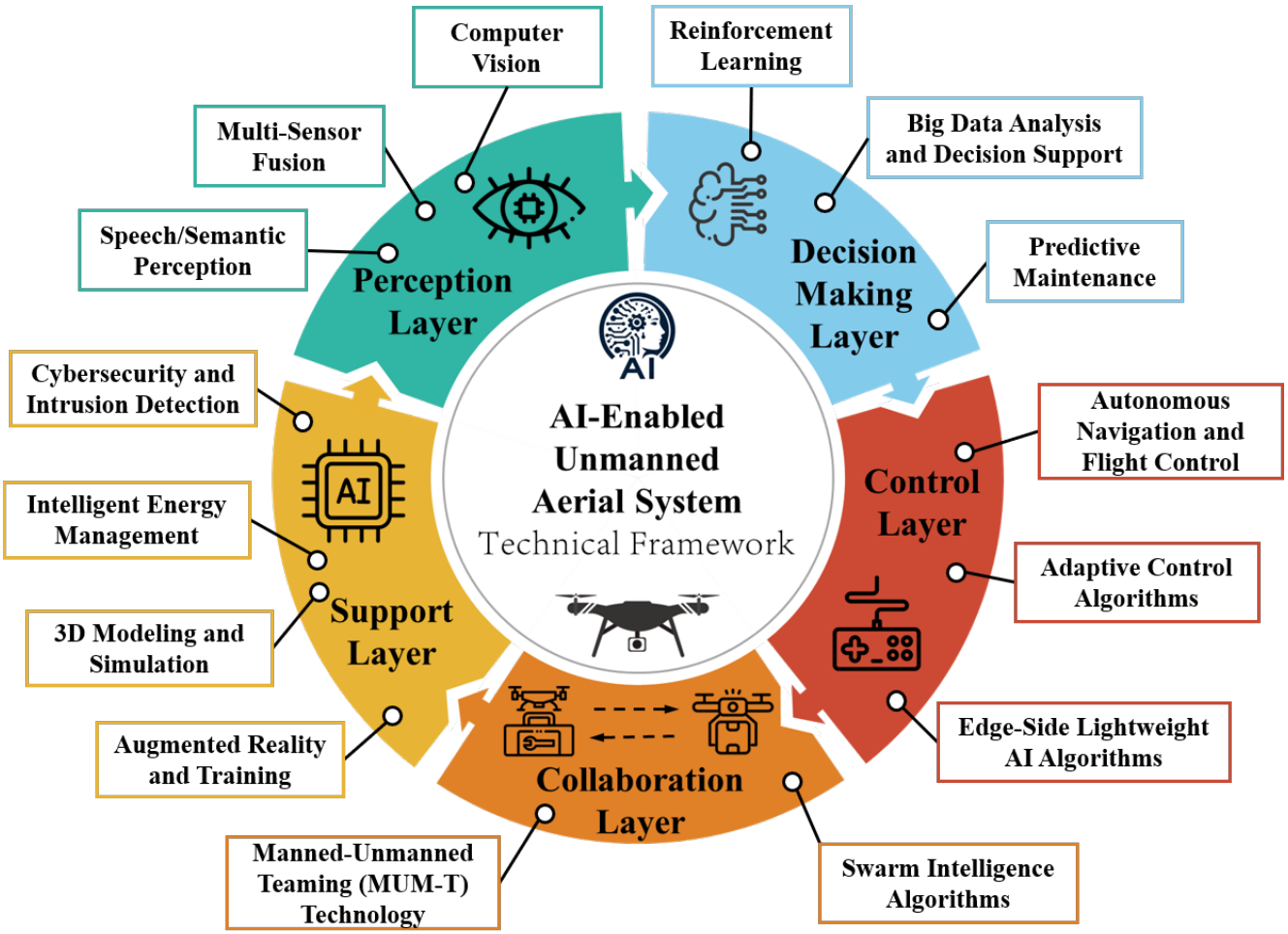


Figure 3. The core technical framework of AI-enabled aerial unmanned systems. Source: created by the authors.

aerial images/videos, adapting to perception requirements in scenarios such as low altitude, complex terrain and severe weather. Typical applications include military target reconnaissance, agricultural pest and disease identification, and emergency rescue personnel positioning [70–73]. A representative transformer-based detector for UAV aerial imagery is illustrated in Figure 4.

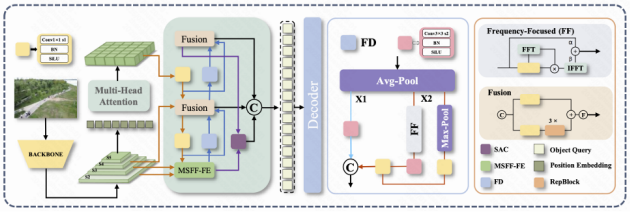


Figure 4. UAV-DETR: a transformer-based object-detection model for UAV aerial images. Reproduced from Ref. [41]. The framework incorporates a multi-scale feature-fusion module with frequency enhancement, a frequency-focused downsampling module, and a semantic-alignment and calibration module to balance spatial and frequency information at different scales.

2. **Multi-Sensor Fusion**: By integrating multi-source sensor data (e.g., vision, Light Detection and Ranging (LiDAR), Inertial Measurement Unit (IMU), and GPS), AI algorithms incorporated with Bayesian estimation and Kalman filtering are adopted to realize data fusion. This enhances the accuracy and robustness of environmental perception, and addresses the perception failure of a single sensor in scenarios such as occlusion, strong light, and loss of GPS signals [42, 43].

3. **Speech/Semantic Perception**: Natural Language Processing (NLP) technology enables natural interaction between UAVs and operators, supporting voice command control, which is applicable to high-intensity operation scenarios such as emergency rescue [58, 74].

4.2 Decision-Making Layer Technology: Intelligent Decision-Making in Complex Scenarios

The decision-making layer acts as the "brain" of aerial unmanned systems. Its core objective is to realize intelligent decision-making (e.g., path planning, task

scheduling, and fault decision-making) based on data from the perception layer. The core AI technologies include:

1. **Reinforcement Learning**: Reinforcement Learning algorithms enable autonomous decision-making, path planning and control of UAVs in complex dynamic environments, solving the problem of insufficient adaptability of traditional algorithms in unknown environments and dynamic obstacle scenarios [44].

2. **Big Data Analysis and Decision Support**: AI can process and analyze large volumes of data collected by unmanned equipment—including images, video and sensor data—to provide decision-makers with real-time intelligence and decision support [60, 75].

3. **Predictive Maintenance**: Time series analysis, Long Short-Term Memory (LSTM) networks and other algorithms are used to analyze UAV flight data and sensor status, identify equipment faults and performance degradation in advance, reduce the probability of unplanned downtime, and improve system reliability [76, 77].

4.3 Control Layer Technology: High-Precision Autonomous Flight Control

The control layer functions as the "hands and feet" of aerial unmanned systems. Its core objective is to achieve high-precision and high-stability autonomous flight control based on instructions from the decision-making layer, adapting to different flight platforms and operation scenarios. The core AI technologies include:

1. **Autonomous Navigation and Flight Control**: AI technology empowers unmanned equipment with autonomous navigation and flight control capabilities. Through integrated sensors and algorithms, UAVs can execute complex flight missions and path planning without direct human control [44, 45, 48, 49, 52, 53, 78, 79]. An end-to-end approach to high-speed autonomous flight is illustrated in Figure 5.

2. **Adaptive Control Algorithms**: AI algorithms such as fuzzy control and neural network control realize real-time adjustment of UAV flight parameters, addressing the insufficient control accuracy of traditional control algorithms in scenarios such as wind speed changes, load alterations, and airframe attitude deviations.

3. **Edge-Side Lightweight AI Algorithms**: Advanced AI control algorithms are deployed on UAV edge-side chips through technologies such as model pruning, quantization, and distillation. This meets computing power requirements while reducing energy consumption, enabling real-time and low-latency flight control [54].

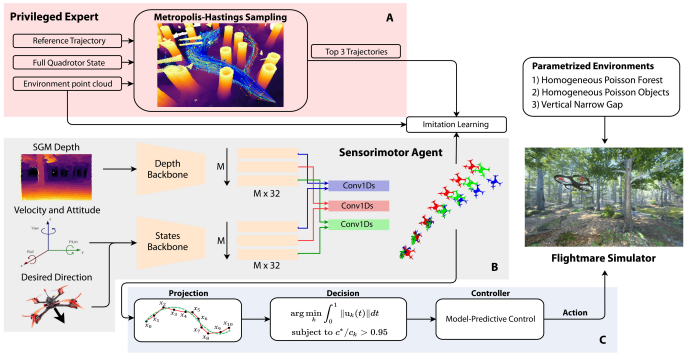


Figure 5. An end-to-end approach for high-speed autonomous quadrotor flight with onboard sensing and computation. Reproduced from Ref. [52]. The method learns a sensorimotor mapping with a convolutional network trained in simulation through privileged learning.

4.4 Collaboration Layer Technology: Intelligent Collaborative Operation of Multi-UAVs

The collaboration layer is the core for aerial unmanned systems to upgrade from "single-UAV operation" to "swarm operation". Its core objective is to realize distributed collaboration and swarm control of multiple UAVs to complete complex tasks that cannot be achieved by a single UAV. The core AI technologies include:

1. **Swarm Intelligence Algorithms**: Driven by AI algorithms, multiple unmanned devices can achieve collaborative operation and form intelligent swarms to execute complex tasks, such as joint strikes by swarm UAVs or coordinated distribution by logistics UAVs [55, 56, 59, 80–83]. A cooperative aerial manipulation system enabled by proximal multi-drone collaboration is shown in Figure 6.

2. **Manned-Unmanned Teaming (MUM-T) Technology**: AI algorithms realize collaborative operation between human, manned aircraft and UAVs, optimize task allocation strategies, allow operators to focus on high-level decision-making, and assign frontline operation tasks to UAVs. This is applicable to scenarios such as military operations and low-altitude traffic management [85, 86].

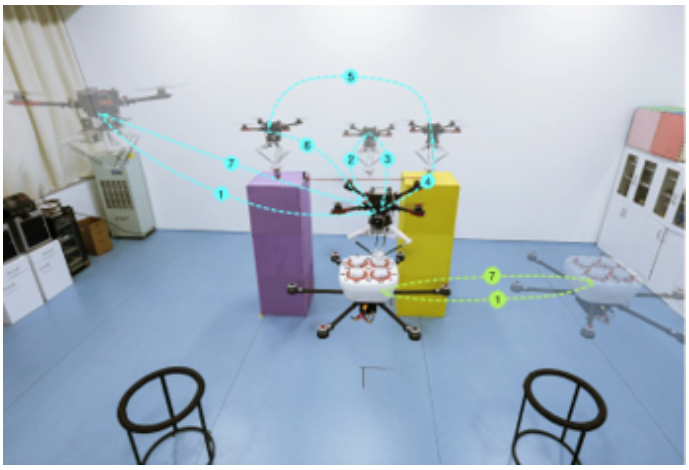


Figure 6. FlyingToolbox, a cooperative aerial manipulation system with sub-centimetre-level docking accuracy under vertical-stack flight conditions, suggesting a new model for heterogeneous and interactive flying robot cooperation in diverse applications. Reproduced from Ref. [84].

4.5 Support Layer Technology: Safe and Efficient Operation of the System

The support layer is the foundation for the large-scale application of aerial unmanned systems. Its core objective is to achieve communication security, data security, and energy consumption optimization, providing support for technologies at all levels. The core AI technologies include:

1. **Cybersecurity and Intrusion Detection**: Generative Adversarial Networks (GANs), deep learning and other algorithms are used to identify malicious attacks and data leakage behaviors in UAV communication links, building a deep defense system. This is applicable to military UAVs and classified civil UAV scenarios [11, 15, 87–89].

2. **Intelligent Energy Management**: AI algorithms optimize the power output strategy of UAVs, and plan the optimal operation path based on flight tasks and remaining power to improve endurance capacity. Trajectory optimization under time and energy constraints further enables efficient data collection in time-sensitive environmental monitoring missions [90–92].

3. **3D Modeling and Simulation**: AI algorithms help to construct and generate virtual operation scenarios to conduct simulation testing and optimization of UAV flight behavior and operation performance, reducing the cost of physical aircraft testing and accelerating practical deployment [93].

4. **Augmented Reality and Training**: The combination of AI and unmanned equipment can create realistic training environments for military and civilian simulation training, enhancing the authenticity and effectiveness of training programs [94, 95].

4.6 System-Level Integration and Cross-Layer Interactions

While the previous subsections discuss the perception, decision-making, control, collaboration, and support layers individually, the practical performance of an AI-enabled UAV is determined by their interaction as a closed-loop system rather than by the local accuracy of any single module. This subsection therefore reframes the technical framework from a system-level perspective, addressing three questions that recur throughout the SLR corpus: (a) how do AI components interact at runtime, (b) how do errors propagate across layers, and (c) what mission-level performance metrics best capture this coupling.

1. **Closed-loop interaction between layers**: In a representative UAV stack, the perception layer feeds state estimates and semantic maps to the decision-making layer, which produces high-level commands (waypoints, target assignments, recovery actions) that are then tracked by the control layer through the actuator stack. Collaboration and support layers act in parallel, providing inter-agent information and ensuring communication, energy, and cyber integrity. The latency budget of this loop is tight: for agile flight, perception–decision–control must close in tens of milliseconds, which constrains the choice of AI models more strongly than their offline accuracy alone (cf. Table 3). Recent end-to-end approaches such as learned navigation policies in cluttered environments [52, 53] and language-conditioned action policies on UAVs [58, 60, 93] explicitly collapse this loop into a single learned mapping, trading interpretability for latency.

2. **Error propagation and failure modes**: Because the layers are cascaded, a small perception error—e.g. a misclassified obstacle under glare, a degraded depth estimate during GPS-denied flight [42], or a momentarily poor detection on a transformer-based aerial detector [41]—can amplify through planning into an unsafe trajectory and finally into a control transient that violates flight envelope limits. Similarly, communication or synchronization errors at the

collaboration layer can desynchronize multi-UAV decisions, even when each UAV's local controller is nominally correct [56, 82]. AI-specific failure modes—out-of-distribution inputs and image corruptions [40], adversarial perturbations, distributional shift and reward-misspecification effects [47], and hallucinations of LMM-based agents—compound classical failure modes (sensor noise, actuator saturation), motivating the cybersecurity and intrusion-detection efforts discussed in the support layer [87–89] and the operational design domain (ODD) approach to scoping ML safety arguments [96].

3. **Mission-level impact**: The relevant figures of merit are therefore not module-level metrics (mAP, MSE) alone, but mission-level KPIs: success rate on a defined mission, mean-time-between-interventions, energy per delivered task, and constraint-violation rate. AI components influence overall system performance through three coupling mechanisms: (a) *capability coupling*, where better perception unlocks new decision policies (e.g. aggressive flight in clutter); (b) *budget coupling*, where each AI module competes for the same compute, memory, and energy envelope; and (c) *trust coupling*, where the worst-performing or least-explainable component bottlenecks the certification of the whole system. Practical integration challenges, including hardware–software co-design, deterministic scheduling on heterogeneous SoCs, and the gap between simulation and field deployment, are picked up again in Section 7.

5 Applications and Engineering Practices of AI in Aerial Unmanned Systems

The integration of AI and aerial unmanned systems has enabled large-scale engineering applications in both military and civilian sectors, giving rise to a number of representative engineering cases and commercialized products. This section combines corresponding application scenarios with integrated engineering cases and representative products, to analyze the implementation pathways and application values of AI technologies in various scenarios.

To go beyond a purely descriptive enumeration, each application is examined along four analytical dimensions that map directly onto the layered framework of Section 4 and answer RQ2–RQ3: (a) the dominant AI technique employed, (b) the specific operational problem they address, (c) the qualitative or quantitative performance gain reported in the literature, and (d) the current technical limitations and open challenges. Where the underlying studies report quantitative figures (e.g. detection accuracy, time savings, energy or emission reduction), these are reproduced explicitly; otherwise, qualitative assessments are made transparent so that demonstrated impact and anticipated impact remain clearly distinguishable.

5.1 Applications in Military Domain

Military aerial unmanned systems represent a pivotal application scenario for AI technology, with core demands encompassing autonomous combat, collaborative reconnaissance, and precision strike. The integration of AI has substantially enhanced the battlefield adaptability, combat efficiency, and personnel safety of military unmanned systems. Typical engineering cases and applications are as follows:

1. **Autonomous Air Combat**: In April 2024, the U.S. Air Force and DARPA reported AI-driven autonomous air-combat tests using the X-62A VISTA aircraft [97]. The AI system performed high-speed aerial combat maneuvers against manned F-16 fighter jets, demonstrating autonomous tactical decision-making in a constrained flight-test setting (Figure 7(a)). *Technique*: deep reinforcement learning and self-play training of tactical policies, supervised by safety constraints. *Problem solved*: sub-second tactical decisions in beyond-visual-range and within-visual-range engagements, where human reaction time can become a bottleneck. *Reported gain*: according to U.S. Air Force and DARPA program releases, closed-loop dogfight maneuvering was performed against a piloted F-16, and the official communications report that the engagement was conducted without test-pilot override. *Limitations*: narrow training distribution, limited explainability, and lack of an agreed certification framework for lethal autonomy.

2. **Autonomous Formation Flight**: In December 2025, Baykar reported through a company release what it described as the first fully autonomous close-formation flight of the Kizilelma unmanned combat aerial vehicle (UCAV) [98]. Relying on smart-fleet autonomy algorithms and real-time data sharing, the reported test demonstrated coordinated maneuvering between multiple UCAV prototypes (Figure 7(b)). *Technique*: multi-agent

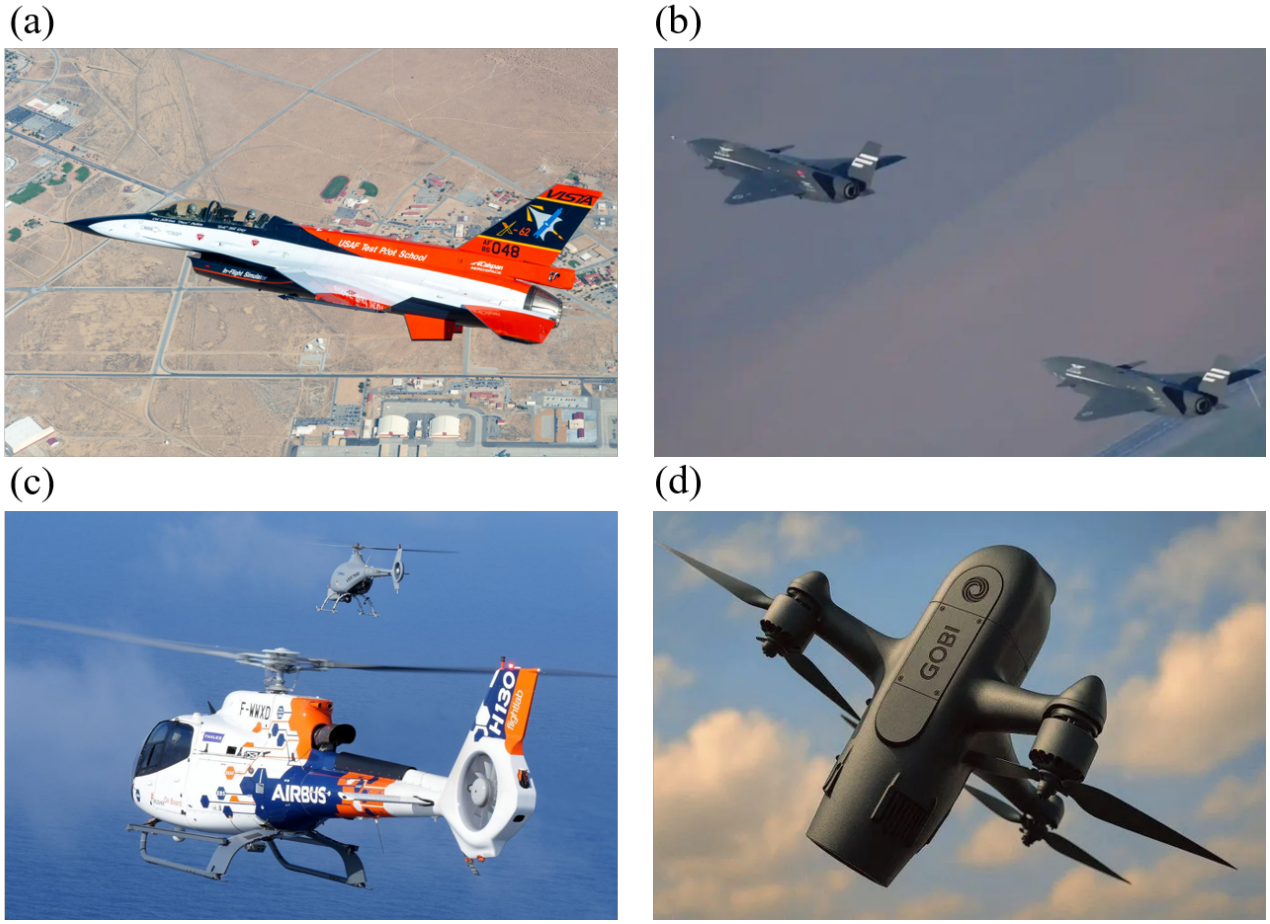


Figure 7. Representative engineering cases of intelligent unmanned systems in the military domain. (a) X-62A VISTA aircraft used in the DARPA Air Combat Evolution (ACE) program, source: U.S. Air Force/AFRL official release [97]; (b) Bayraktar Kizilelma unmanned combat aerial vehicle conducting formation flight using smart fleet autonomy, source: Baykar official press release [98]; (c) MUSHER manned-unmanned teaming demonstration involving the H130 FlightLab and VSR700 unmanned aerial system, source: Airbus official press release [99]; (d) GOBI high-speed drone interceptor, source: Harmattan AI official product webpage [100].

control with learned formation policies and low-latency wireless coordination. *Problem solved*: stable close-formation flight at high subsonic speeds without operator-in-the-loop separation control. *Reported gain*: described by the manufacturer as the first publicly reported autonomous close-formation flight of fighter-class UCAVs, and presented as a building block for collaborative combat aircraft (CCA) concepts. *Limitations*: robustness in contested electromagnetic environments and resilience to GNSS/link denial.

3. **Manned-Unmanned Teaming Combat**: In October 2024, Airbus Helicopters and its European partners reported a full-scale Manned-Unmanned Teaming (MUM-T) demonstration under the MUSHER project in France and Italy [99]. The demonstration provided evidence of interoperability among multiple manned and unmanned platforms in a shared network (Figure 7(c)). *Technique*: AI-assisted task allocation, cross-platform datalinks, and shared situational awareness. *Problem solved*: reducing operator workload while extending sensor and weapon reach across heterogeneous manned/unmanned formations. *Reported gain*: interoperability was demonstrated across multiple national platforms in a full-mission scenario, which is a prerequisite for broader deployment. *Limitations*: regulatory fragmentation across NATO airspace and immature trust-calibration tools for human operators.

4. **Anti-UAV Operations**: In 2025, Harmattan AI publicly introduced the GOBI high-speed interceptor drone for counter-UAV operations [100]. The system is described by the company as enabling rapid interception of low-altitude Group 1–2 UAS threats, including loitering munitions

Table 4. AI applications in civilian aerial unmanned systems: typical scenarios, technologies, and representative products.

Civilian Application Scenarios	Core AI Technologies	Representative Products/Enterprises	Application Values
Precision Agriculture	Computer Vision, Big Data Analysis	DJI AGRAS T100S, AeroVironment Agricultural UAVs	Achieve accurate identification of diseases and pests, variable fertilization/pesticide application, improve agricultural production efficiency, and reduce consumption of chemical fertilizers and pesticides [102].
Logistics and Distribution	Reinforcement Learning (Path Planning), Autonomous Flight Control	JD JDX-50 Logistics UAV, Zipline Medical Supplies Delivery UAV	Realize autonomous delivery of last-mile logistics, solve the problem of material transportation in remote areas and disaster-stricken regions [103].
Emergency Rescue	Computer Vision, Multi-UAV Collaboration	DroneSense, LEMUR S Search and Rescue UAV	Quickly access dangerous areas to realize personnel positioning and on-site data transmission, improve rescue efficiency and personnel safety [104–106].
Infrastructure Inspection	Computer Vision (Fault Diagnosis), Predictive Maintenance	Skycatch, Percepto	Realize automated inspection of power facilities, bridges and pipe networks, improve inspection accuracy, and reduce labor costs and operational risks.
Low-Altitude Security	Target Tracking, Swarm Intelligence Collaboration	Shield AI, DJI Industry Edition UAVs	Realize autonomous regional patrol and abnormal target identification, applicable to urban security and border patrol.
Remote Sensing and Mapping	Computer Vision, 3D Modeling	Applied Aeronautics Albatross UAV, Scale	Realize high-precision topographic mapping and 3D modeling, applicable to geological exploration and urban planning.

(Figure 7(d)). *Technique*: onboard CNN-based detection coupled with model-predictive trajectory estimation; radar-based UAV detection in clutter environments provides a complementary sensing modality for low-altitude threat identification [101]. *Problem solved*: short-warning interception of low-radar-cross-section targets where ground-based air defense may be too slow or costly. *Reported gain*: according to company statements and defense-industry reports, the per-interceptor cost is claimed to be substantially lower than that of short-range surface-to-air missiles for comparable slow-mover threats; this cost comparison still requires independent benchmarking. *Limitations*: false-positive risk in cluttered urban airspace and sensitivity to adversarial visual perturbations.

5.2 Applications in Civilian Domain

Civilian aerial unmanned systems apply AI mainly to efficiency improvement, cost reduction, and scenario expansion, covering agriculture, logistics, emergency rescue, infrastructure inspection, and related fields. Several commercial products and pilot deployments have been reported, and typical applications and representative products are listed in Table 4.

Beyond this synthetic mapping, the four-dimension lens introduced at the start of this section provides a more technical reading of civilian deployments:

1. **Precision agriculture** relies primarily on CNN/Transformer-based detectors trained on multispectral aerial imagery to localize disease and weed patches; recent reviews report variable-rate input savings of roughly 20–30% for fertilizer and pesticide compared with uniform application [107], while deep-learning models reach mean F1-scores above 0.9 for several crop-disease classes on UAV-based aerial imagery [39]. Limitations include limited generalization across crops, growth stages, and lighting conditions [102].

2. **Last-mile logistics and medical delivery** increasingly combine autonomous UAV platforms with route-optimization methods, including graph-based vehicle routing and deep-RL path planning. Field deployments in Rwanda, Ghana, Malawi, and Vanuatu show substantial reductions in delivery times and improvements in availability for blood products, vaccines, and diagnostic samples; in Rwanda, drone delivery

of blood products achieved a mean delivery time of approximately 50 minutes, roughly 79 minutes faster than road transport on average, with time savings of up to 211 minutes in the most remote facilities [108]. Remaining barriers include weather robustness, BVLOS regulatory approval, payload/range constraints, and battery endurance [103].

3. **Search-and-rescue** applications combine small-object detectors (e.g. DETR-style transformers [105], evaluated on aerial benchmarks such as VisDrone [38]) with multi-UAV cooperative coverage [104, 106]; consistent improvements in target-detection probability and area-coverage time per mission are reported, but communication-link fragility and limited night-time perception remain open issues.

4. **Infrastructure inspection** adopts CNN-based fault classifiers and predictive-maintenance models on edge platforms (e.g. Skycatch, Percepto) to convert manual inspection workflows into automated digital-twin updates, typically reducing inspection labour cost while raising defect-recall on power lines, bridges, and pipelines; calibration drift across sites and the cost of labelled defect data are recurring limitations.

5. **Low-altitude security and remote sensing/3D mapping** similarly leverage tracking, swarm coordination, and learned 3D reconstruction to enable autonomous patrols and high-resolution surveying, with current limitations in privacy compliance, photogrammetric accuracy under non-Lambertian surfaces, and multi-session data fusion. Across all civilian categories, three recurring bottlenecks emerge: (a) domain shift between training and field data, (b) the gap between offline accuracy benchmarks and onboard real-time performance, and (c) the need for application-specific certification, which is treated systematically in Section 7.

5.3 AI-Driven Decarbonization and Sustainable Operations

Beyond conventional military and civilian mission effectiveness, the integration of AI with aerial unmanned systems is becoming a practical pathway for supporting decarbonization-oriented operations. Building on the technical architecture in Figure 3, perception, intelligent decision-making, and autonomous control jointly support low-emission flight operations and high-resolution environmental monitoring. This coupling allows UAV systems not only to reduce mission-level operational energy use, but also to function as decision-support infrastructure for climate-related monitoring and governance. Here, we distinguish demonstrated AI-enabled optimization benefits from broader system-level sustainability impacts, the latter of which depend on explicit lifecycle boundaries.

At the platform and operational levels, AI contributes to eco-efficient UAV design, intelligent energy management, and carbon-aware mission planning. Recent studies show that embedded intelligence combined with renewable-energy-aware design can improve sustainability in urban logistics operations [109]. In addition, AI-assisted power management for electric and hybrid solar UAVs improves endurance and energy utilization, while its lifecycle-emission benefits depend on assumptions regarding manufacturing, charging electricity, battery replacement, and maintenance [91]. On the operational side, optimization algorithms under carbon-related constraints can reduce route-level emissions in UAV logistics, while multi-agent deep reinforcement learning enables climate-aware trajectory planning at network scale [57, 110]. These results mainly demonstrate mission-, route-, or network-level optimization benefits rather than complete lifecycle decarbonization.

AI-enabled UAVs also provide strong support for emissions monitoring and energy transition scenarios. With multi-modal sensing and deep learning models, UAV-based cyber-physical systems can identify and quantify methane emissions in field conditions, offering actionable evidence for greenhouse-gas mitigation [111]. In parallel, intelligent drone inspection improves the reliability of wind turbine operation and helps reduce downtime in renewable-energy systems [112]. Similar approaches have been extended to building-envelope assessment, where UAV sensing and AI analysis jointly identify thermal leakage and guide targeted retrofitting [113]. These applications provide monitoring and decision-support benefits, while the final sustainability impact depends on subsequent mitigation, maintenance, or retrofit actions.

Another emerging direction is AI-assisted carbon-sink assessment. By combining UAV imagery (e.g., RGB and LiDAR) with machine-learning-based estimation, recent methods improve the speed and accuracy

of aboveground biomass and forest carbon-stock evaluation compared with traditional field-only workflows [114]. This strategy is being expanded to urban green-space analysis, where UAV-based 3D vegetation reconstruction supports policy-facing estimation of urban carbon-sink capacity [115]. Overall, AI-enabled aerial unmanned systems are evolving from mission tools into climate-relevant decision-support tools for low-carbon aviation and sustainable territorial management, provided that their system-level impacts are evaluated with transparent lifecycle assumptions.

Algorithmic challenges: balancing climate constraints with operational safety. A point that emerges clearly from the corpus, but is rarely made explicit, is that AI-driven decarbonization in aerial unmanned systems is ultimately a constrained multi-objective optimization problem: minimizing energy or CO_2 per mission while simultaneously satisfying safety, mission-success, and regulatory constraints. The technical mechanisms can be grouped into four families, each with its own algorithmic trade-off:

1. **Energy-aware trajectory and mission planning**: Optimization-based formulations (e.g. improved grey-wolf and metaheuristic algorithms under carbon-tax constraints [110]) and multi-agent deep reinforcement learning over network-level traffic flows [57] explicitly trade flight-time/throughput against fuel or contrail-induced climate impact. The core difficulty is that the climate-optimal policy may violate operational manageability: [57] reports that aggressively climate-optimal trajectories increase potential conflicts in dense traffic, requiring conflict-resolution layers (TD3-based) to keep operations feasible. The algorithmic challenge is therefore to design safety-constrained or Pareto-aware RL that exposes the climate–throughput–safety frontier rather than collapsing it into a single objective. Constrained Markov decision processes and constrained policy optimization [50], surveyed comprehensively in [46] and benchmarked in [51], provide a principled algorithmic foundation for this trade-off, although their application to network-scale UAV traffic remains an open research direction.

2. **Embedded intelligence for eco-efficient platforms**: On the platform side, AI-augmented designs combining brushless DC motors, LiPo batteries, and perovskite solar cells with deep Q-network energy allocation have demonstrated up to roughly 18% reduction in energy consumption and 12% increase in covered area for the same charge under realistic urban-canyon and field conditions, while keeping structural safety factors above 1.5 under gust loading [109]. Hybrid solar/electric propulsion strategies further extend endurance for long-duration target tracking and inspection [91, 92]. The remaining algorithmic challenge is robust online adaptation when load, wind, and irradiance distributions shift between training and field deployment.

3. **UAV-based emissions monitoring and verification**: Deep-learning-based methane quantification from UAV-borne hyperspectral and gas sensors enables localization and flux estimation of fugitive emissions in oil/gas and agricultural settings, providing measurable evidence for mitigation [111]. Drone-based wind-turbine and building-envelope inspection [112, 113] similarly improves the reliability of low-carbon assets by reducing downtime and enabling targeted retrofits. The algorithmic difficulty here is uncertainty quantification: regulatory acceptance requires not only point estimates but calibrated confidence intervals, which most off-the-shelf deep models do not natively provide.

4. **Carbon-sink assessment from aerial sensing**: ML-based biomass and carbon-stock estimation from UAV RGB/LiDAR [114] and 3D vegetation reconstruction in urban green spaces [115] reduce the cost and turnaround of carbon accounting compared with field-only protocols. Open challenges include cross-site transferability of learned allometric relationships, domain shift between sensors and ecosystems, and traceability for MRV (measurement, reporting, verification) compliance.

Across these four mechanisms, three transverse algorithmic challenges recur and define a research agenda for AI-driven decarbonization of UAVs: (a) safety-constrained learning [46, 50, 51], where reward shaping and constraint formulations must encode hard envelope, separation, and mission constraints rather than only soft penalties; (b) lifecycle-level objectives, in which AI policies should report end-to-end energy or emissions under explicit boundaries, including manufacturing, charging, battery replacement, and maintenance, rather than mission-only proxies; and (c) verifiability, requiring that climate-relevant

claims (energy savings, CO_2 or CH_4 reductions) be reproducible and auditable, which in turn calls for benchmark datasets, standardized KPIs, and uncertainty-aware models. These directions are picked up again as cross-cutting research priorities in Sections 6 and 7.

6 Development Trends of AI-Driven Aerial Unmanned Systems

AI is reshaping aerial unmanned systems not only at the algorithmic level, but also at the operational and organizational levels. In civil aviation, AI-assisted route optimization, flight-data analytics, and smart-civil-aviation roadmaps illustrate how digital technologies are being integrated into operational management and air traffic systems [116]. In the UAV sector, the convergence of AI with 5G/6G communications, edge computing, and digital twins is expected to support higher autonomy, more scalable coordination, and safer low-altitude operations.

Taken together, the reviewed literature suggests a consistent direction: AI is improving operational efficiency, safety, resource allocation, and environmental monitoring, while also creating new demands for certification, robustness, and governance. The following trends are therefore presented as evidence-informed projections rather than deterministic predictions.

To make these trends actionable rather than aspirational, each item below is qualified by the following three dimensions: *Technical pathway*—the algorithmic or hardware enablers most likely to drive the trend; *Maturity*—a coarse readiness level (research, prototype, early deployment, mainstream) consistent with the SLR corpus; and *Key challenges*—the main remaining barriers, which feed naturally into the analysis of Section 7. These maturity levels are assigned using simple corpus-based criteria rather than a formal technology-readiness assessment: *research* denotes capabilities reported only in simulation or laboratory settings, without field trials; *prototype* denotes integrated demonstrations on real platforms in controlled or otherwise constrained environments; *early deployment* denotes limited operational use in real missions, by a small number of operators or under restricted regulatory regimes; and *mainstream* denotes routine, commercially available use across multiple operators and missions. Each label reflects the most advanced stage demonstrated in the retained corpus and is intended as a coarse indicator only.

1. **Level of Autonomy**: Moving from manual remote control toward higher levels of supervised autonomy, AI enables aerial unmanned systems to improve perception, decision-making, and control in partially known or dynamic environments, and to complete selected end-to-end tasks with reduced human intervention [59, 117–121]. *Technical pathway*: hierarchical RL, learned end-to-end policies, neural flight envelope protection, and human–AI shared-control schemes. *Maturity*: prototype to early deployment for racing-class agility and SAE-style autonomy levels 3–4 in narrow missions; mainstream for assisted (level 1–2) flight. *Key challenges*: certified out-of-distribution behavior [40, 47], transparent fall-back logic, and scalable verification and validation, with emerging guidance from regulatory bodies [122] and ODD-based ML safety arguments [96].

2. **Edge Computing Power**: With miniaturized computing chips and lightweight algorithms, more AI models can be deployed on UAV edge devices, supporting low-latency real-time decision-making and reducing, rather than fully eliminating, dependence on ground control stations. *Technical pathway:* model pruning/quantization/distillation, neuromorphic and compute-in-memory accelerators [54], and SoC integration with deterministic real-time scheduling. *Maturity*: mainstream for compact CNNs; early deployment for transformer-based perception; research for onboard LMM/VLA inference. *Key challenges*: accuracy/latency/energy trade-offs, thermal budget at altitude, and toolchain fragmentation across embedded platforms.

3. **Swarm Intelligence and Collaboration**: Distributed collaboration and autonomous task allocation of multi-UAV swarms are expected to expand in large-area environmental monitoring, emergency rescue, military operations, and other scenarios. *Technical pathway*: multi-agent deep RL (MADDPG, MAPPO), graph neural network-based task allocation, decentralized SLAM and exploration [56, 82], and resilient mesh communications. *Maturity*: prototype to early deployment in defense and large-scale inspection; research for >1,000-agent civilian swarms. *Key challenges*: non-stationary training, link denial and EMI resilience, and airspace integration of large coordinated formations.

4. **Intelligent Aviation**: Embodied intelligence

and large models may become important decision-support components for aerial unmanned systems, enabling multi-modal perception, natural language interaction, data analysis, and complex task planning under constrained operating conditions [57, 123]. *Technical pathway*: climate-aware trajectory optimization via multi-agent RL [57], anomaly-detection LSTMs for predictive maintenance, and unsupervised deep learning for flight-data analytics [123]. *Maturity*: early deployment in airline route optimization and predictive maintenance; research for fully integrated cognitive flight management. *Key challenges*: data scarcity for rare events, regulatory acceptance of learned components in safety-critical loops, and integration with legacy ATM stacks. A representative multi-agent deep RL framework for climate-friendly trajectory planning is shown in Figure 8.

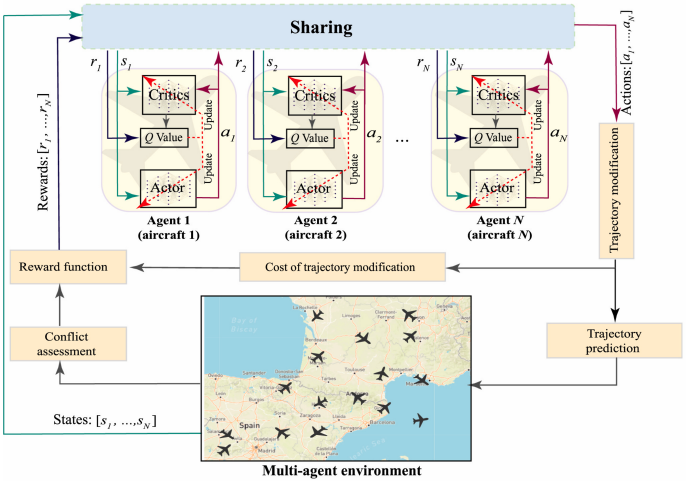


Figure 8. A cooperative decision-making framework using multi-agent deep reinforcement learning for operationally feasible climate-friendly trajectory planning. Reproduced from Ref. [57] under the CC BY-NC-ND 4.0 license. The framework uses twin delayed deep deterministic policy gradient (TD3) to adjust trajectories and resolve potential conflicts associated with climate-optimal routes.

5. **New Application for Embodied Intelligence**: Emerging embodied-AI architectures use large models as high-level decision-support modules for unmanned systems, enabling multi-modal task understanding and planning while leaving low-level control to conventional or learned controllers [58, 74, 124]. *Technical pathway*: embodied LMMs/VLMs as cognitive cores, vision–language–action policies on UAVs [60, 93], and agent frameworks like AeroAgent that pair LMMs with low-level controllers [58]. *Maturity*: mostly research; first prototypes demonstrated in indoor and constrained outdoor settings. *Key challenges*: onboard inference cost, hallucination/grounding errors in safety-critical contexts, and lack of agreed evaluation protocols for embodied agents. The AeroAgent framework, which pairs an LMM-based cognitive agent with a low-level drone controller, is illustrated in Figure 9.

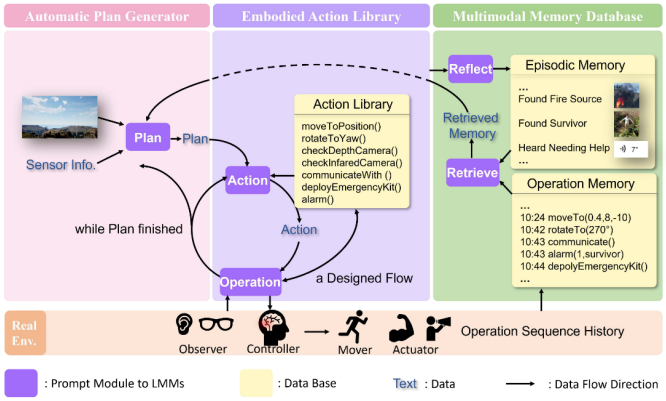


Figure 9. AeroAgent, an agent framework tailored for industrial drone technology that harnesses the power of Large Multimodal Models (LMMs), outperforms existing Deep Reinforcement Learning (DRL)-based agents in experimental evaluations, which highlights the advantages of embodied LMMs in complex real-world scenarios. Reproduced from Ref. [58].

6. **Applications of Generative AI in the Civil Aviation Industry**: Generative AI can process civil aviation data and support scenario generation, trajectory synthesis, and simulation-assisted planning for airports and airlines [125–127]. *Technical pathway*: LLM-based scenario generation [125], transferable generative models for aircraft trajectories [126], and conditional diffusion models for trajectory synthesis [127]. *Maturity*: prototype with academic validation. *Key challenges*: factual fidelity, simulation-to-reality transfer, and acceptability for safety-critical training and decision support.

7. **Low-Altitude Economy**: Aerial unmanned systems will be fully integrated into the low-altitude economy, achieving commercial deployment in low-altitude logistics, low-altitude tourism, Urban Air Mobility (UAM), urban governance and other scenarios, becoming the core carrier of the low-altitude economy. *Technical pathway*: integrated U-space/UTM stacks, AI-based traffic flow management, 5G/6G-assisted communications, and shared digital twins [128]. *Maturity*: early deployment for last-mile logistics; pilot operations

for UAM. *Key challenges*: airspace integration with manned aviation, public acceptance and noise, and harmonized international rules.

8. **Low-Carbon Development**: Supported by AI-based intelligent flight control and energy consumption optimization, aerial unmanned systems will further reduce energy consumption and carbon emissions, and replace more traditional high-emission operations, becoming an important technical means to achieve global carbon neutrality [110]. *Technical pathway*: carbon-aware optimization [110], multi-agent RL for climate-friendly trajectories [57], AI-driven eco-design of UAV platforms [109], and UAV-based emissions monitoring [111]. *Maturity*: early deployment for energy management and inspection; research for system-of-systems carbon optimization. *Key challenges*: verifiable life-cycle accounting, harmonized MRV protocols, and avoiding rebound effects from increased UAV activity.

9. **Military Applications**: AI technologies have been explored or deployed in military scenarios including data analysis, autonomous logistics, and bio-inspired robotic networks, with reported benefits for situational awareness, logistics support, and mission planning in specific settings [129–131]. *Technical pathway*: AI-assisted ISR fusion, bio-inspired swarm tactics [131], and decision-support agents for commanders [130]. *Maturity*: early to mainstream deployment in surveillance and decision support; prototype for fully autonomous engagement. *Key challenges*: meaningful human control, international humanitarian law compliance, and resilience to electronic and cyber warfare.

7 Multidimensional Challenges in the Integration of AI with Aerial Unmanned Systems

The application of AI in the aerospace sector offers substantial opportunities, but it also introduces technical, regulatory, ethical, and operational risks.

7.1 Technical Challenges

Technical challenges represent the core bottleneck in the AI-enabled integration of aerial unmanned systems, mainly arising from the complexity of UAV operating environments, limited onboard resources, and stringent requirements for system reliability. Specific challenges are as follows:

1. **Insufficient complex-environment perception capability**
In occluded scenes, strong light, GPS denial, severe weather and other complex scenarios, the perception accuracy and robustness of UAVs decrease significantly. The data fusion efficiency and anti-interference ability of multi-sensor fusion still need to be improved.

2. **Difficult deployment of edge-side AI algorithms**
UAV edge-side platforms are characterized by limited computing power, energy sensitivity, and small storage space. The lightweight transformation of high-level AI models still suffers from problems such as accuracy loss and excessive latency, which can hardly meet the demands of real-time control.

3. **Insufficient reliability and explainability of autonomous decision-making**
The "black-box nature" of AI algorithms makes their decision-making processes difficult to interpret, which brings huge risks in safety-critical scenarios such as flight safety and military operations. Meanwhile, AI exhibits insufficient decision-making fault tolerance in unknown scenarios and is prone to decision errors.

4. **Insufficient consistency and stability of multi-UAV collaboration**
Technical difficulties still exist in communication delay, data synchronization, and task allocation for multi-UAV swarms. In dynamic environments, the consistency and stability of swarm collaboration are difficult to guarantee, leading to problems such as formation dispersion and task conflicts.

5. **Restriction of AI applications by endurance and payload capacity**
The integration of AI increases the demand for UAV computing power and energy consumption. However, the lagging development of battery technology makes it difficult for UAV endurance and payload capacity to meet the requirements of high-level AI applications, limiting the operational radius and task complexity.

6. **Prominent cyber and data security risks**
The networked and intelligent development of aerial unmanned systems exposes them to cyber security risks such as malicious intrusion, data leakage, and command tampering. Especially for

military UAVs and classified civilian UAVs, such risks directly affect operational safety and national interests.

7.2 Non-technical Comprehensive Challenges

The application of artificial intelligence technology in aerial unmanned equipment has driven technological innovation and opened up broader application prospects, while also posing multiple non-technical comprehensive challenges, including technology integration, data security, regulation formulation, interpretability, talent cultivation, capital investment, market acceptance, business model innovation, industry collaboration, airworthiness and credibility, and human-machine collaboration. For instance, integrating intelligent unmanned systems into existing aerospace systems requires addressing issues of technology integration and compatibility to ensure inter-system collaboration.

In critical flight control and safety domains, it is imperative to ensure the high reliability of intelligent unmanned system technologies and enhance their environmental adaptability and ability to complete complex tasks—a fundamental prerequisite for their widespread application. It is also essential to safeguard the security of flight data and prevent data leakage or unauthorized access. Regulatory authorities need to formulate relevant regulations to ensure the safety and compliance of intelligent unmanned systems and advance technological standardization, thereby facilitating their global application and cooperation. In the future, it will be necessary to develop new airworthiness standards and regulations to mitigate the risks brought by emerging technologies and ensure operational safety. Overcoming these challenges demands the joint efforts and collective wisdom of all stakeholders within and outside the industry.

1. **Regulatory and Standard Formulation**: Relevant regulations and standards remain to be improved to ensure the legitimacy and compliance of AI technology [19, 132, 133], with regulators starting to publish concrete certification guidance for ML-based aviation components [122].

2. **Technical Interpretability and Trust Issues**: It is necessary to improve the interpretability of AI models and address trust-related issues [128, 134], including the use of operational design domain (ODD) specifications to scope ML safety arguments [96] and explicit accounting for AI failure modes such as distributional shift [40, 47].

3. **Talent Cultivation and Professional Skills**: The industry faces a shortage of professional talents, and it is imperative to strengthen talent cultivation and the improvement of professional skills.

4. **Investment and Cost Pressures**: The development of Smart Civil Aviation requires huge investment, and it is necessary to explore diversified financing channels [135, 136].

5. **Market Acceptance and Demand**: Enhance market awareness of and demand for the application of AI technology [9, 10].

6. **Business Model Innovation**: New service-oriented and logistics-driven business models—such as AI-powered drone delivery platforms and UAV-as-a-service frameworks—are reshaping how unmanned aerial systems are commercialized and deployed [137–139].

7. **Industry Collaboration and Integration**: Strengthen industry collaboration and integration, and establish an effective communication and cooperation platform [116, 140].

8. **Airworthiness and Credibility**: AI technology must pass airworthiness and credibility verification to establish public trust [141–143].

7.3 Interdisciplinary Challenges

Interdisciplinarity plays a pivotal role in the development of intelligent unmanned equipment, covering multiple fields such as aerospace engineering, computer science, data science, communication technology, mechanical engineering, meteorology, regulation formulation, human-machine interaction, economics, and materials science [144–146]. The integration of these disciplines drives advancements in UAVs in terms of autonomous flight control, target recognition and tracking, data analysis and decision support, and intelligent swarm collaborative operation. It also provides multi-dimensional perspectives and solutions for addressing challenges including technology integration, data security, regulation formulation, and talent cultivation. Current interdisciplinary challenges are as follows:

1. **Shortage of interdisciplinary talents**: The field demands interdisciplinary talents who master both aviation engineering and control technology, as well as artificial intelligence and big data. At present, the talent training system in universities is still discipline-oriented, with insufficient

interdisciplinary talent cultivation, making talent shortage a core development bottleneck.

2. **Insufficient interdisciplinary research collaboration**: Disciplines such as aviation engineering, computer science, and materials science have different research paradigms and evaluation systems. Interdisciplinary research faces great difficulties in funding support and achievement transformation, making it hard to produce systematic interdisciplinary research outcomes.
3. **Insufficient integration of technology and humanities & social sciences**: The development of aerial unmanned systems involves not only technical issues but also ethical, legal, social governance and other humanities and social science issues. At present, the integration of technical research and humanities & social science research is insufficient, making it difficult to address the ethical and social challenges brought by intelligent unmanned systems.

8 Conclusions and Prospects

The rapid evolution of AI-driven aerial unmanned systems marks a profound paradigm shift in the aerospace sector, transitioning from automated execution to cognitive autonomy. This transformation is fueled by the deep interdisciplinary convergence of aerospace engineering, computer science, and communication technologies, which has collectively expanded the boundaries of intelligent flight.

AI-enabled aerial unmanned systems may contribute to carbon-neutrality efforts by improving energy management, trajectory optimization, and environmental monitoring in specific mission contexts. However, their broader sustainability benefits should be evaluated under explicit lifecycle boundaries, including manufacturing, charging electricity, maintenance, and end-of-life treatment. Looking ahead, the integration of renewable energy sources with AI-based optimization may further improve the environmental performance of UAV operations, provided that such benefits are verified through transparent and reproducible assessment.

However, realizing this vision requires overcoming multidimensional challenges, including technical maturity, data security, and regulatory compliance. The dedicated discussion on AI-driven decarbonization in Section 5 further indicates that future progress depends on jointly advancing intelligent flight, trustworthy governance, and climate-oriented deployment strategies. Future developments will likely depend on the synergy between Embodied AI and International Standardization. It is through the collective wisdom of global stakeholders and robust cross-border cooperation that AI-enabled UAVs will ultimately achieve their dual promise: driving cutting-edge technological progress while safeguarding our planet's environmental future.

Data Availability Statement

Not applicable.

Funding

This work was supported without any funding.

Conflicts of Interest

Zenglin Liu is affiliated with the POLY Aviation Technology Co., Ltd., Beijing 100027, China. The authors declare that this affiliation had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

AI Use Statement

The authors declare that ChatGPT-5 was used for language editing, including improvements to the language, grammar, and readability of the manuscript. The authors have carefully reviewed, revised, and verified the AI-assisted output and take full responsibility for the content of the manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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