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Abstract

Unmanned Aerial Vehicles (UAVs) have evolved from remotely controlled platforms into intelligent networked systems capable of autonomous decision making and automation across a wide range of application areas. This transformation was possible due to advances in artificial intelligence, wireless communication, and edge computing. Despite these advances, research on AI-enabled UAVs remains fragmented, with most works focusing on technical details or single application domains, frequently ignoring the interplay of autonomy, communication topology, and governance at the ecosystem level. This article presents a framework-driven review of AI-enabled UAV ecosystems to fill this gap. Combining scoping with narrative synthesis, the review proposes three analytical frameworks to organize the literature. The Mission-Stack-Context (MSC) framework characterizes the relationship between missions, systems, and contexts. The AI Integration Maturity Model for UAVs (AIMM-UAV) evaluates the progression from basic manual integration to advanced autonomy. And the Energy-Autonomy Budget (EAB) framework looks into whether the energy resources can support the

desired levels of autonomy. These frameworks together help to unearth typical design patterns, compromises, and constraints across different sectors, including agriculture, healthcare logistics, public safety, and infrastructure inspection. The article also identifies future research directions, including the need for ecosystem-level autonomy, energy-aware AI, and governance frameworks that can keep pace with technological advances.

Keywords: Artificial Intelligence, Unmanned Aerial Vehicles, Autonomous Systems, AI Governance, UAV Ecosystems, Autonomy Maturity Models.

1 Introduction

Unmanned Aerial Vehicles (UAVs), or drones as they are popularly known, are potentially one of the most change-inducing and innovative technology platforms in the recent years. The progression of these devices has been largely influenced by the significant development in Artificial Intelligence (AI), robotics, Internet of Things (IoT), wireless communication, and sensing technologies. Consequently, UAVs are being equipped with advanced functionalities that they can hardly be human-mediated, e.g., they can carry out complex tasks such as multi-target monitoring, agile navigation in unpredictable environments, and real-time decision-making during critical missions[1]. The initial concept of a stealth technology for military surveillance has been superseded by the drone’s ascendancy in numerous civilian and commercial domains such as precision agriculture, healthcare logistics, environmental conservation, industrial inspection, and disaster response [2, 3].

Due to the fact that UAVs are turning increasingly capable and self-reliant, they are no longer considered as separate instruments but rather as components of interconnected ecosystems. These ecosystems comprehend various mission requirements, AI technologies, communication networks, and governance rules. In effect, an advanced UAV swarm can coordinate its actions collaboratively in a search-and-rescue mission, whereas medical drones are obliged to observe privacy, safety, and airspace regulations when carrying biological samples. Therefore, the study on UAV has transitioned to the system-of-systems viewpoint that incorporates autonomy, communication, safety, and energy limitations in addition to flight platforms [4, 5].

The research on UAVs has been growing rapidly, but the studies that are available are not cohesive. Several reviews take into consideration only very specific issues like the coordination of the swarm [6], perception algorithms [7], communication architectures [8, 9], and application domains including healthcare, humanitarian response, and environmental monitoring [10–12]. Other papers consider the levels of autonomy or communication networks separately, without analysing how these factors influence each other [13–15]. Moreover, very few publications concern the introduction of laws, regulatory frameworks, and ethical requirements that pave the way for the safe use of intelligent UAV systems in real environments [16–18]. The absence of a comprehensive understanding hinders the transfer of knowledge from one sector to another. This, in turn, slows the large-scale implementation of reliable and efficient UAV solutions.

This observation motivates the perspective adopted in this review. Instead of classifying UAV research solely by application area or enabling technology, we consider AI-enabled UAV systems as interconnected ecosystems. Hence and in order to fill the gaps introduced earlier, this review proposes a framework-driven analysis of AI-enabled UAV ecosystems. The objective is to analyse the gradual changes of autonomy and intelligence due to the mission purpose, technology stack, communication architecture, and contextual constraints such as regulation and energy budget. In this regard, we introduce three analytical and interrelated frameworks that help to carry out a domain-structured analysis. The Mission-Stack-Context (MSC) framework that categorizes UAV activities based on the goals of the mission, the artificial intelligence and the hardware/communication side, as well as the external environmental or regulatory constraints. Building on this description, the AI Integration Maturity Model for UAVs (AIMM-UAV) framework evaluates the degree of AI integration, ranging from manually operated platforms to collaborative ecosystem intelligence. Finally, the Energy-Autonomy Budget (EAB) model that connects the computational load, communication needs, and the onboard energy source and shows how the limitation of the endurance affects the autonomy.

The main contributions of this review are summarized as follows:

1. We provide a comprehensive synthesis of recent advances in AI-enabled UAV ecosystems spanning communication, sensing, computation, navigation, cooperative intelligence, governance, and emerging application domains.
2. We introduce the MSC framework for systematically characterizing UAV ecosystems through the complementary dimensions of mission, technology stack, and operational context.
3. We propose the AIMM-UAV and EAB frameworks to evaluate AI integration maturity and resource sustainability as complementary aspects of autonomous UAV system design.
4. We identify current research gaps and discuss future directions toward trustworthy, resource-aware, and ecosystem-centric AI-enabled UAV systems.

Accordingly, this review addresses the following research questions:

- **RQ1:** How can AI-enabled UAV ecosystems be systematically characterized in terms of their missions, technological capabilities, and deployment context?
- **RQ2:** How can the degree of AI integration and autonomy maturity be evaluated across heterogeneous UAV systems?
- **RQ3:** How do energy, computation, sensing, and communication constraints influence the sustainability of increasing UAV autonomy?
- **RQ4:** What technological, organizational, and governance challenges must be addressed to achieve trustworthy, scalable, and ecosystem-level UAV intelligence?

The remainder of this paper is organized as follows. Section 2 presents the review methodology and evidence synthesis approach. Section 3 introduces the conceptual foundations of AI-enabled UAV ecosystems, including autonomy, communication architectures, AI modules, and governance considerations. Sections 4, 5, and 6 present the three proposed analytical frameworks: the MSC framework, the AIMM-UAV,

and the [EAB](#) framework. Section 7 synthesizes findings across application sectors through the lens of these frameworks, highlighting recurring architectural patterns, autonomy levels, and deployment challenges. Section 8 examines governance, trustworthiness, safety, and regulatory considerations for intelligent [UAV](#) ecosystems, and closes with future research directions toward ecosystem-level autonomy, resource-aware intelligence, and trustworthy governance. Finally, Section 9 concludes the paper.

2 Review Methodology: Hybrid Scoping and Narrative Approach

The topic of [AI-enabled UAVs](#) is fragmented across multiple disciplines including robotics, autonomous systems, wireless communications, edge computing, healthcare, industrial automation, and regulatory policy. As such, the literature is scattered across different research communities, each using its own terminology and evaluation criteria. To address this challenge, this article adopts a hybrid methodology that combines the breadth of a scoping review with the interpretive depth of a narrative synthesis. Narrative approaches, when conducted transparently, are recognized as rigorous and useful for synthesizing complex, heterogeneous bodies of evidence, especially when the aim is conceptual integration rather than effect estimation [19, 20].

The specific goal of this review is not to aggregate performance metrics across incomparable benchmarks, but to identify recurring concepts, architectural trends, and research gaps across heterogeneous studies in order to construct a framework-driven understanding of [AI-enabled UAV](#) ecosystems able to link (i) [AI](#) capabilities and autonomy mechanisms, (ii) communication/control topologies, and (iii) governance and assurance constraints across sectors.

This review article includes a total of 94 references, of which 89% are scientific journal articles that have been peer reviewed, 7% are conference proceedings, and the remaining 4% are standards, regulatory documents, books, and technical reports. The predominance of journal articles reflects the mature state of the research on [AI enabled UAV](#) autonomy, communication architectures, and edge intelligence. Conference papers mostly represent the research directions that are rapidly evolving and changing, such as multi-[UAV](#) coordination, learning-based control, and aerial edge computing. To help the technical analysis reflect the current governance, safety, and regulatory aspects of the real-world [UAVs](#) deployment, a few authoritative non-academic sources were purposely included.

2.1 Review Design and Rationale

In this review, we treat autonomy as a system-level property emerging from interactions among onboard intelligence, inter-[UAV](#) coordination, and ground, edge, and cloud orchestration, rather than as a single algorithmic choice. Recent [UAV](#) surveys illustrate the importance of this perspective. Reviews of aerial communications and edge computing show that latency, intermittent connectivity, and resource constraints materially shape what autonomous functions can be executed onboard and which be offloaded [21, 22]. Similarly, surveys of autonomous multi-[UAV](#) networks and [UAV](#)

assisted wireless communications show that coordination mechanisms, communication conditions, and network assumptions strongly influence operational feasibility and reliability [9, 23].

Accordingly, a scoping design was used to ensure broad capture of technical and applied evidence, and a narrative synthesis was used to support cross-sector interpretation of (a) recurring architectural patterns, (b) trade-offs among energy/compute/communication reliability, and (c) constraints imposed by assurance and governance. This combination is consistent with contemporary guidance that scoping reviews can legitimately prioritize mapping and concept clarification; while acknowledging the interpretive role of synthesis in complex, multi-dimensional evidence bases [24, 25].

2.2 Evidence Identification and Selection

The literature search was conducted across IEEE Xplore, Scopus, Web of Science, and PubMed. These databases were selected because together they cover engineering, telecommunications, computer science, healthcare, and operational applications. Because terminology varies substantially across sectors and research communities, literature identification followed an adaptive, modular strategy rather than a single monolithic keyword regime. This decision is aligned with the "Tailored Approach" literature-search model for complex reviews, which emphasizes the practical need to adapt searching to multi-dimensional evidence landscapes [26].

Operationally, the adaptive strategy was implemented by aligning identification activities with the paper's major thematic blocks (autonomy and AI mechanisms; sectoral ecosystems; communication topologies; governance and assurance). The intent was to reduce systematic omissions caused by vocabulary mismatch (e.g., "swarm coordination" vs. "fleet management", "BVLOS authorization" vs. "operational risk assessment", "edge intelligence" vs. "aerial MEC"). Publications from 2022 onward were prioritized to reflect post-2022 acceleration in learning-enabled autonomy, aerial edge computing integration, and the increased prominence of governance instruments relevant to AI-enabled aviation systems.

2.3 Analytical Framework and Data Synthesis

Screening was conducted in two stages: title and abstract screening, followed by full-text review. The inclusion boundaries were refined iteratively to maintain consistency with the cross-sector and topology-driven objectives of the review.

After the literature was collected, each included study was examined according to four complementary dimensions. These dimensions were selected because they identify key factors influencing the design and operation of intelligent UAV systems. They also reflect the methodological gap observed in many recent UAV reviews [21, 22, 27, 28].

1. Mission context and application sector (e.g., agriculture, medical/humanitarian logistics, industrial inspection, urban operations, defense/security);
2. AI capabilities and autonomy mechanisms (e.g., perception, decision making, learning, multi-agent coordination);

3. Communication and coordination topologies (e.g., centralized, decentralized, hybrid, edge-assisted, swarm-based);
4. Governance, safety, and assurance requirements (e.g., regulatory compliance, risk assessment, security protocols).

To ensure analytical comparability, a minimum chartability criterion was applied during full-text screening. A study was retained only when sufficient information was available to map it to at least two of the four charting dimensions. Borderline cases were reassessed against the same criterion to avoid the inclusion of studies that could not contribute meaningfully to the cross-dimensional synthesis.

Following data charting, narrative synthesis was used to identify recurring patterns, differences, and trade-offs across the included studies. The charted evidence was then organized through the three proposed analytical frameworks. The [MSC](#) framework was used to examine relationships among mission requirements, technical architecture, and operating context; [AIMM-UAV](#) was used to assess the maturity of [AI](#)-enabled autonomy; and [EAB](#) was used to analyze the energy, computational, and communication constraints associated with increasing autonomy.

2.4 Governance and Regulatory Sources

Academic publications alone do not fully capture the governance challenges associated with autonomous [UAV](#) systems. For this reason, the review also considers regulatory frameworks and standards that influence the practical deployment of [AI](#)-enabled [UAVs](#) systems.

The regulatory sources include the [National Institute of Standards and Technology \(NIST\)](#) Artificial Intelligence Risk Management Framework (AI RMF), the European Union Artificial Intelligence Act, the European Union Aviation Safety Agency (EASA) Artificial Intelligence Roadmap, and the Federal Aviation Administration (FAA) Beyond Visual Line of Sight (BVLOS) initiatives [16, 17, 29, 30]. These documents are not analyzed as technical contributions but are used to place the surveyed research within its broader regulatory and governance context.

2.5 Limitations

This hybrid methodology provides broad conceptual coverage and supports cross-sector integration, but it also introduces limitations. Because the review uses an adaptive, modular identification strategy rather than a single fixed global search string, the resulting corpus should be interpreted as a representative mapping of the [AI-UAV](#) ecosystem rather than an exhaustive enumeration of all relevant publications. This trade-off is consistent with the purpose of scoping reviews in complex domains, which prioritize concept clarification and evidence mapping over completeness for meta-analysis [24, 25].

Selection bias is possible because we prioritized studies with clear architectural commitments and extractable ecosystem implications. However, this is a deliberate bias toward interpretability: framework-driven synthesis cannot be performed reliably on papers that omit control assumptions, coordination structure, or deployment constraints.

3 Conceptual Foundations of AI-Enabled UAV Ecosystems

The capabilities of modern UAVs have expanded considerably over the past decade. What were once primarily remotely piloted platforms are now able to perceive their environment, process large amounts of data, and make autonomous decisions during mission execution. This evolution has been driven by advances in AI, sensing technologies, wireless communications, and IoT infrastructures, opening the door to applications ranging from environmental monitoring and infrastructure inspection to healthcare logistics and emergency response [31].

As UAV applications have become more sophisticated, the focus has gradually shifted from individual aircraft to complete operational ecosystems. A typical deployment may involve multiple UAVs, terrestrial communication networks, edge and cloud computing resources, human operators, and regulatory constraints working together to accomplish a common objective [32, 33]. Looking at UAVs from this broader perspective helps explain why system performance hinges on communication, resource management, and coordination across the entire ecosystem, and not on onboard intelligence alone.

The purpose of this section is to introduce the concepts that underpin the analytical frameworks developed later in the paper. We first discuss UAV ecosystems as cyber-physical systems, followed by the role of AI in enabling autonomy. We then review communication architectures, resource management considerations, and the governance issues that influence the deployment of autonomous UAV systems.

3.1 UAV Ecosystems as Cyber-Physical Systems

Modern UAVs are viewed as Cyber-Physical Systems (CPSs) that integrate sensing, computation, communication, and control within a unified operational environment. Beyond the aerial platform itself, UAV ecosystems often include ground control stations, edge servers, cloud infrastructures, communication networks, and external data sources that collectively support mission execution and decision making. Information continuously flows among these components, enabling perception, localization, navigation, task allocation, and operational monitoring, as reflected in Rahman et al.'s classification of multi-UAV path-planning algorithms coordinating aerial platforms toward shared mission objectives [33].

From a systems perspective, UAV ecosystems can be viewed as multi-layer architectures composed of physical, cyber, and organizational dimensions. The physical layer includes aerial platforms, sensors, and actuators. The cyber layer encompasses data processing, communication, and intelligent decision-making functions. The organizational layer incorporates mission objectives, human operators, stakeholders, and regulatory constraints, a layer for which Almuraqab et al. provide empirical grounding, showing that public trust and social influence, more than cost, shape acceptance of AI-enabled drone services [32]. This layered perspective highlights that the effectiveness of a UAV deployment depends as much on the interactions among the broader ecosystem components as on the capabilities of individual platforms.

As UAVs become significantly integrated into smart cities, industrial operations, and public services, ecosystem-level considerations such as interoperability, scalability, resilience, and governance become critical design objectives. As a result, many studies advocate moving beyond platform-centric perspectives toward ecosystem-oriented models that capture interactions among aerial, terrestrial, and cloud-based resources [34–36].

3.2 Artificial Intelligence and Autonomy

AI has become one of the main factors behind the growing autonomy of UAV systems. Rather than simply automating predefined tasks, modern AI techniques allow UAVs to interpret sensor data, reason under uncertainty, adapt to changing environments, and improve their behaviour through experience. These capabilities have expanded the range of missions that can be performed with limited or no continuous human intervention.

Within UAV ecosystems, AI capabilities generally support three interconnected functions: perception and situational awareness, decision making and control, and adaptive learning. Perception functions transform raw sensor data into actionable information through techniques such as object detection [34, 35], semantic segmentation, tracking, localization, and environmental mapping [37]. Because no single sensor is reliable under all operating conditions, data from cameras, radar, Light Detection and Ranging (LiDAR), and inertial and satellite navigation sensors are fused to build a robust and consistent representation of the operating environment [37].

Decision-making and control functions convert environmental awareness into operational actions. These functions include path planning, obstacle avoidance, task allocation, resource management, and multi-agent coordination. Recent advances in Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), and multi-agent learning have significantly improved the ability of UAVs to operate in dynamic and uncertain environments while reducing dependence on continuous human supervision, as surveyed by Frattolillo et al. across coverage, search, offloading, communication, and navigation tasks [38].

A third category of capabilities focuses on adaptive learning and long-term improvement. Techniques such as continual learning, transfer learning, and Federated Learning (FL) allow UAVs to update models and policies based on mission experience while reducing communication overhead and preserving privacy. These approaches support knowledge reuse across missions and enable adaptive forms of autonomy [39, 40]. In this vein, Li et al. propose a privacy-preserving federated learning framework for space–air–ground integrated networks that combines differential privacy, adaptive transfer learning, and bi-level reinforcement learning to address data heterogeneity and device dynamics across satellite, aerial, and ground nodes [41].

Despite these advances, increasing autonomy introduces new challenges related to robustness, explainability, verification, and accountability. Consequently, AI is both an enabler of autonomy and a source of new engineering and governance requirements.

3.3 Communication and Coordination Topologies

Reliable communication is essential for almost every intelligent UAV application. Whether a UAV exchanges information with a ground station, nearby aerial platforms, edge servers, or cloud services, communication enables collaborative sensing, distributed decision making, resource sharing, and mission coordination.

Several communication architectures are commonly observed in UAV deployments. Centralized architectures rely on communication with a Ground Control Station (GCS) or cloud infrastructure for mission coordination and decision support. Decentralized architectures distribute intelligence among individual UAVs, enabling local decision making and increased resilience to communication failures. Hybrid architectures combine both approaches by leveraging onboard intelligence together with support from Mobile Edge Computing (MEC) platforms and cloud services. Ahmad et al. characterize this same centralized-decentralized-hybrid taxonomy for UAV surveillance systems, noting that architecture choice depends on deployment scale, mission complexity, latency requirements, and connectivity reliability [42].

Recent advances in next-generation wireless networks have further expanded the communication capabilities of UAVs. Technologies such as 5G, emerging 6G systems, and advanced aerial networking paradigms facilitate seamless integration between aerial and terrestrial networks while supporting low-latency communication, distributed intelligence, and large-scale multi-UAV operations, as surveyed for cellular-connected 5G/B5G UAV integration by Mishra and Natalizio [43] and for 6G ultra-reliable low-latency UAV networks by Masaracchia et al. [44].

As UAV deployments evolve toward swarm-based systems, communication and autonomy become notably interdependent. The location of intelligent decision-making functions, whether onboard, at the network edge, or within the cloud, directly influences latency, reliability, scalability, and operational resilience. Consequently, communication topology represents a fundamental design dimension for autonomous UAV ecosystems [36].

3.4 Energy Constraints and Resource Management

Limited onboard energy continues to be one of the main constraints on UAV autonomy. Flight, sensing, wireless communication, onboard processing, and payload operation all compete for the same battery resources, meaning that improvements in one capability often come at the expense of another. The growing integration of AI further amplifies these challenges. Advanced perception models, Deep Learning (DL) inference, distributed coordination mechanisms, and communication-intensive operations can significantly increase energy consumption. Therefore, resource management has emerged as a critical research area aimed at balancing intelligence, communication performance, and operational endurance.

Several strategies have been proposed to address these constraints, including energy-aware mission planning, adaptive communication protocols, lightweight AI models, and task offloading through MEC infrastructures. These approaches seek to optimize the allocation of computational and communication resources while maintaining acceptable levels of autonomy and mission performance [45, 46]. Understanding

the relationship between intelligence, communication, computation, and energy consumption is therefore essential for the design of scalable and sustainable UAV ecosystems.

3.5 Governance, Safety, and Trustworthiness

The increasing deployment of autonomous UAVs in public and commercial environments has elevated the importance of governance, safety, security, and trustworthiness. Beyond technical performance, successful deployment depends on regulatory compliance, public acceptance, cybersecurity, privacy, and accountability mechanisms that are integrated into system architecture from the outset rather than imposed after design.

Safety is a primary concern for urban and Beyond Visual Line of Sight (BVLOS) operations, requiring systematic risk assessment, operational authorization, and safety assurance. For example, the Federal Aviation Administration (FAA)’s proposed BVLOS rule introduces risk-based operational categories, mandatory safety management systems, and structured reporting requirements [47]. The growing use of AI adds challenges around transparency, explainability, bias, and verification; building on its earlier roadmap [48], European Union Aviation Safety Agency (EASA) has since issued detailed guidance on AI explainability, human-AI cooperation, and safety risk assessment for AI-based aviation systems [49].

Cybersecurity is equally critical, as communication links, sensors, software, and supporting infrastructure may be targeted by jamming, spoofing, data manipulation, or unauthorized access. Reported cases of password theft and GPS jamming and spoofing underscore calls for stronger regulatory and manufacturer-level security standards [50].

These governance, safety, and security considerations form an essential foundation for the framework-based analysis presented in the following sections.

4 Mission–Stack–Context (MSC) Framework

AI-enabled UAV research now covers a wide range of missions, technologies, and deployment scenarios. Studies span wireless communications [9], edge computing [45, 46], integrated sensing and communication [51], autonomous navigation [50], swarm intelligence [36], and many application-specific domains. Although this diversity has accelerated innovation, it has also made it more difficult to compare UAV systems using existing technology- or application-oriented classifications.

As UAV ecosystems become more autonomous and interconnected, understanding individual technologies in isolation is no longer sufficient. Similar missions may employ fundamentally different AI capabilities, communication architectures, and resource-management strategies, while identical technological stacks may exhibit very different behaviors depending on the deployment environment. Consequently, a broader analytical perspective is required to explain how autonomy emerges from the interaction between mission objectives, technological capabilities, and contextual constraints.

This motivates the proposed MSC framework, which organizes AI-enabled UAV ecosystems according to three complementary dimensions:

- **Mission:** the operational objectives pursued by the UAV system.
- **Stack:** the technological subsystems enabling mission execution.
- **Context:** the environmental, operational, and governance conditions under which the system operates.

Together, these dimensions provide a structured lens for comparing heterogeneous UAV systems while revealing design trade-offs that may remain hidden in technology-centric analyses.

4.1 Mission Dimension

Mission is the first dimension of MSC because it defines why a UAV system exists. Regardless of the underlying technology, every deployment is ultimately driven by an operational objective. Although many deployments combine multiple functionalities, the surveyed literature reveals five recurring mission objectives that collectively characterize the majority of AI-enabled UAV applications: communication, data collection, computation, sensing, and delivery.

We distinguish what a mission achieves from how it is carried out. Navigation and multi-UAV cooperation are not objectives in themselves: every mission requires navigation, and any mission may be performed by a single platform or a coordinated group. Navigation is thus treated as a capability of the Stack dimension (Section 4.2), and cooperation as an execution mode applying across all objectives (Section 4.1.6). This keeps the MSC dimensions non-overlapping and lets cooperative intelligence be assessed explicitly via AIMM-UAV (Section 5).

4.1.1 Communication Missions

Communication missions position UAVs as aerial networking assets that extend wireless coverage, enhance network capacity, or restore connectivity in infrastructure-constrained environments. In such deployments, UAVs may operate as aerial base stations, relays, cache-enabled platforms, or temporary access points serving terrestrial users and IoT devices. Typical objectives include improving wireless coverage and quality of service through the placement of aerial base stations [52, 53], restoring or extending connectivity in underserved areas through relay platforms [54], increasing network capacity and offloading traffic in hotspot scenarios [55], reducing end-to-end latency through adaptive routing [56], and delivering content efficiently through cache-enabled UAVs [57]. These objectives often need to be achieved simultaneously despite rapidly changing network conditions and limited onboard resources.

Addressing these challenges requires intelligent and adaptive decision making. Hence, recent research has focused on machine learning and reinforcement learning techniques for dynamic UAV deployment, trajectory planning, routing, spectrum allocation, caching, and resource management. In [23], the authors survey reinforcement-learning-based approaches across autonomous multi-UAV wireless networks, covering resource allocation, trajectory planning, mobile edge computing, and network security. In [56], the authors propose an adaptive UAV-assisted geographic routing scheme that combines Q-learning with fuzzy-logic path calculation to improve packet delivery

and reduce end-to-end delay in vehicular networks. These advances are helping transform UAVs from passive communication relays into intelligent network nodes capable of autonomously adapting to dynamic wireless environments.

4.1.2 Data Collection Missions

Data collection missions treat UAVs as mobile sinks responsible for gathering information from distributed sensors and IoT devices. Such deployments are particularly relevant in large-scale monitoring applications where direct communication with fixed infrastructure is impractical or energy inefficient [46, 58]. Major objectives include minimizing data collection delay while ensuring reliable information delivery [58], reducing information staleness through Age of Information optimization [59], enabling timely data collection using DRL [60], and jointly optimizing data freshness and energy consumption in coordinated multi-UAV sensing missions [61].

Recent work combines trajectory optimization with learning-based scheduling and mobility control to adapt data collection strategies to dynamic sensing environments while maintaining mission endurance. In [62], the authors use multi-agent deep reinforcement learning to jointly optimize UAV trajectory, transmission scheduling, and access control for energy-efficient sensing-data collection. In [61], the authors employ multi-agent deep Q-learning to optimize the trajectories of data-collecting and energy-transmitting UAVs, jointly minimizing age of information and energy consumption.

4.1.3 Computation Missions

Computation-oriented missions use UAVs as mobile edge platforms that bring processing resources closer to latency-sensitive users. Such systems support task offloading, distributed inference, and real-time services in areas where fixed computing infrastructure is unavailable or insufficient. Existing work focuses on UAV-assisted edge architectures [21, 45], joint offloading and resource allocation [22, 63], and the extension of edge services to space-air-ground integrated networks [64]. The main difficulty lies in coordinating communication, computation, mobility, and energy decisions under limited onboard resources.

Unlike communication missions, where networking performance is the primary concern, computation missions emphasize execution latency, resource utilization, and computational efficiency. This leads to tighter integration between networking, scheduling, and resource management functions.

4.1.4 Sensing and ISAC Missions

Sensing missions focus on acquiring and interpreting information from the physical environment using visual, radar, LiDAR, thermal, hyperspectral, and wireless sensing technologies. Representative applications include surveillance, infrastructure inspection, precision agriculture, environmental monitoring, mapping, and search-and-rescue operations [12, 42]. More recently, Integrated Sensing and Communication (ISAC) has emerged as a promising paradigm in which sensing and wireless communication share spectrum and hardware resources. This integration can improve spectral efficiency

while bringing perception and communication functions into a common system architecture, both for low-altitude UAVs [51, 65, 66] and for high-altitude platform-assisted designs [67].

The value of these missions lies not only in collecting data, but in converting it into actionable situational awareness. AI-based perception methods, including DL, computer vision, multimodal sensor fusion, and object detection, are therefore used to extract high-level semantic information from raw measurements and support autonomous decision making [34, 35]. In ISAC-enabled deployments, this process also introduces trade-offs among sensing accuracy, communication quality, computational workload, and spectrum use, making joint and adaptive resource management particularly important.

4.1.5 Delivery and Logistics Missions

Delivery missions use UAVs to transport physical payloads such as parcels, medical supplies, laboratory samples, and emergency aid. Unlike the preceding objectives, in which the UAV delivers a communication, computation, or information service, delivery missions move mass, so payload weight directly constrains flight range, energy consumption, and the number of deliveries per sortie. Recent reviews of last-mile parcel delivery report substantial potential reductions in emissions and cost compared with ground vehicles, while also noting that routing and scheduling, charging infrastructure, and energy consumption remain open problems and that experimental validation is still limited [68]. In healthcare and humanitarian settings, delivery missions support the rapid transport of medical supplies to remote or disaster-affected areas, where time savings can be operationally significant [10, 11].

AI is increasingly used to address the combinatorial and dynamic nature of these missions. Deep reinforcement learning has been applied to assign packages to drones and coordinate multi-agent delivery at scale [69], and to construct energy-aware routes that integrate drone energy-consumption models into the learned policy [70]. Delivery missions are also among the most exposed to societal and regulatory constraints, since they typically require BVLOS operation over populated areas; public trust has been shown to be a decisive factor in the acceptance of AI-enabled drone delivery services [32].

4.1.6 Execution Mode: Single-UAV, Multi-UAV, and Swarm Operations

Each of the five mission objectives can be carried out by a single UAV or by a coordinated group of platforms. Examples in the surveyed literature include multi-UAV data collection with jointly learned trajectories [61, 62], cooperative target search [36], swarm redeployment after platform failures [6], cooperative swarm localization [71], and multi-agent delivery [69]. Cooperation can improve spatial coverage, mission speed, redundancy, and resilience to the failure of individual platforms.

These benefits come at the cost of greater coordination complexity. Multi-UAV and swarm operations must contend with synchronization, communication overhead, partial observability, distributed decision making, and fault tolerance, and cooperative

Table 1 Principal mission objectives identified in AI-enabled UAV ecosystems. Execution mode is a cross-cutting attribute that applies to every objective.

Mission Objective	Primary Purpose	Representative Characteristics
Communication	Provide wireless connectivity and network services	Aerial base stations, relays, caching platforms, coverage extension, adaptive routing [52–57]
Data Collection	Gather information from distributed sensing infrastructures	Mobile data harvesting, IoT integration, trajectory optimization, AoI minimization [58–62]
Computation and Edge Intelligence	Provide edge computing and AI processing capabilities	Task offloading, resource allocation, latency reduction, edge intelligence [21, 22, 63, 64]
Sensing and ISAC	Perceive the physical environment, possibly while supporting communications	Surveillance, monitoring, mapping, target detection, integrated sensing and communication [12, 42, 51, 65–67]
Delivery and Logistics	Transport physical payloads to target locations	Last-mile parcel delivery, medical and humanitarian supply, package-drone assignment, energy-aware routing [10, 68–70]
<i>Execution mode (cross-cutting)</i>	Determine whether a mission is performed by one or several coordinated UAVs	Single-UAV, multi-UAV, and swarm operation; task allocation, formation control, distributed decision making [6, 36, 38, 71]

formations introduce new attack surfaces such as position spoofing [72]. Multi-agent RL, distributed optimization, and cooperative path planning have therefore become central tools for adaptive cooperation and collective decision making [23, 33, 38].

Within MSC, execution mode is treated as an attribute of a mission rather than as a mission in its own right. The same data collection objective, for example, may be pursued by one UAV following a precomputed route or by a swarm that jointly adapts its trajectories online. The difference lies not in what the system is meant to achieve but in how much coordinated intelligence it requires, which is precisely what AIMM-UAV characterizes in Section 5.

The five mission objectives are not mutually exclusive, and practical deployments often combine several of them. A search-and-rescue operation, for example, may combine sensing, communication, and computation objectives executed by a cooperating swarm, while a medical delivery service may pair a delivery objective with communication support for BVLOS command and control. Nevertheless, the objectives capture the dominant operational purposes found in the surveyed literature and provide a useful basis for comparing otherwise heterogeneous AI-enabled UAV systems. Table 1 summarizes these mission objectives together with the cross-cutting execution mode.

Table 2 Principal stack layers identified in AI-enabled UAV ecosystems.

Stack Layer	Primary Function	Representative Components
Sensing and Perception	Acquire and interpret environmental information	Cameras, radar, LiDAR , GNSS, inertial sensors, sensor fusion, computer vision models [7, 34, 35]
Communication and Networking	Enable information exchange among ecosystem entities	A2A/A2G links, cellular networks, satellite communications, mesh networking, ISAC, routing protocols [8, 9, 51, 67]
Computation and Edge Intelligence	Process data and execute AI algorithms	Onboard processors, MEC servers, cloud computing platforms, edge AI, machine learning models [14, 23, 77]
Decision Making and Control	Transform information into operational actions	Trajectory planning, reinforcement learning, resource allocation, autonomous control, task scheduling, swarm coordination [6, 36, 74, 75]
Energy and Resource Management	Optimize resource utilization and mission endurance	Battery management, power allocation, energy-aware scheduling, charging, energy harvesting, resource optimization [78–80]
Security, Safety, and Assurance	Ensure trustworthy and compliant operation	Authentication, intrusion detection, cybersecurity mechanisms, safety monitoring, privacy protection, regulatory compliance [13, 16, 81]

4.2 Stack Dimension

Different missions often rely on similar technologies. The Stack dimension therefore focuses on the technological building blocks that enable mission execution. Analysis of the surveyed literature reveals six recurring stack layers: sensing and perception, communication and networking, computation and edge intelligence, decision making and control, energy and resource management, and security, safety, and assurance.

The sensing layer acquires and processes information from onboard and external sources. Communication mechanisms enable information exchange among UAVs, ground stations, edge infrastructures, and cloud resources [73]. Computation layers execute [AI](#) algorithms and support data processing through onboard processors, [MEC](#) platforms, and cloud infrastructures [63, 64]. Decision-making and control layers transform information into operational actions through planning, optimization, and adaptive control mechanisms, including navigation and trajectory planning [71, 72, 74–76].

Energy-management functions regulate resource utilization and mission endurance, while assurance layers address safety, cybersecurity, privacy, and regulatory compliance [16, 17, 27–30]. Importantly, [AI](#) capabilities may be embedded across multiple layers simultaneously, illustrating the pervasive role of intelligence throughout modern UAV ecosystems. Table 2 summarizes the principal stack layers and their corresponding functions.

4.3 Context Dimension

The Context dimension accounts for the external conditions under which a UAV ecosystem must operate. These conditions can alter system performance even when the mission and technological configuration remain unchanged. Unlike mission objectives or architectural choices, many contextual factors evolve during operation and cannot be fully controlled by system designers. Context is therefore distinct from Stack: whereas Stack describes the mechanisms built into the system to manage energy, security, and other concerns, Context describes the external conditions and constraints, such as available energy resources or exposure to threats, that these mechanisms must respond to.

Six recurring forms of context emerge from the surveyed literature. The first three relate directly to the operating environment. Environmental conditions include weather, terrain, physical obstacles, visibility, and propagation characteristics, each of which can affect sensing accuracy, navigation safety, and communication reliability [12, 82]. Network conditions concern topology, connectivity, interference, traffic demand, and spectrum availability [8, 9, 14]. Operational context, in turn, depends on factors such as mission urgency, task complexity, mobility patterns, coordination requirements, and swarm size [6, 10, 11].

Other contextual constraints determine whether a mission can remain sustainable, secure, and practically deployable. Energy limitations arise from battery capacity, payload weight, onboard computation, and the endurance required by the mission [78–80]. Security conditions include exposure to jamming, spoofing, eavesdropping, malware, and adversarial manipulation, as well as the resilience measures needed to preserve trustworthy operation [13, 15, 81]. Governance introduces a different class of constraint: regulatory approval, privacy obligations, safety certification, and ethical requirements may determine whether a technically feasible system can be deployed at all [16–18].

These contextual dimensions are strongly interdependent. Adverse weather may weaken communication links and increase propulsion energy, while a security mechanism may improve resilience at the cost of additional computation and latency. Context should therefore not be treated as background information, but as an active design dimension that shapes mission feasibility and technological choices. Table 3 summarizes the principal contextual dimensions influencing AI-enabled UAV ecosystems.

4.4 Cross-Dimensional Analysis

The value of MSC lies in relating missions, technological capabilities, and deployment conditions rather than considering each dimension independently: mission objectives determine which capabilities are required, stack layers define how those capabilities are realized, and contextual factors determine whether they can be achieved in practice. Communication missions, for example, rely heavily on networking and energy management while remaining sensitive to connectivity and interference; sensing missions depend more on perception and control, tying their performance closely to environmental conditions; and swarm-based deployments require the simultaneous integration

Table 3 Principal contextual dimensions influencing AI-enabled UAV ecosystems.

Context Dimension	Primary Focus	Representative Factors
Environmental Context	Physical operating environment	Weather conditions, terrain characteristics, obstacles, propagation conditions, visibility [12, 82]
Network and Traffic Context	Communication environment and connectivity conditions	Network topology, user density, interference, traffic demand, link quality, spectrum availability [8, 9, 14]
Operational Context	Mission-specific constraints and requirements	Mission urgency, coverage objectives, mobility patterns, task complexity, swarm size [6, 10, 11]
Energy and Resource Context	Availability of operational resources	Battery capacity, payload limitations, computational resources, charging opportunities, edge resources [78–80]
Security and Threat Context	Exposure to cyber and physical threats	Jamming, spoofing, eavesdropping, malware, adversarial attacks, system resilience [13, 15, 81]
Regulatory and Governance Context	Legal, ethical, and compliance requirements	Airspace regulations, privacy constraints, safety certification, ethical considerations, UTM/U-space frameworks [16–18]

of communication infrastructure, distributed intelligence, and operational constraints to support coordinated decision making.

This interaction also explains why identical AI algorithms often perform differently across deployments: an algorithm that succeeds in one application may fail if the technology stack cannot support the required computation or if contextual constraints limit sensing, communication, or energy resources. Figure 1 summarizes this view – rather than treating Mission, Stack, and Context as separate design dimensions, autonomy emerges from their continuous interaction, providing a common reference for comparing heterogeneous AI-enabled UAV systems and identifying design trade-offs.

4.5 Implications for UAV Ecosystem Design

Rather than classifying UAV research by application domain or individual technologies, MSC highlights the relationships among mission objectives, technological architectures, and deployment contexts. This integrated perspective provides a common basis for comparing heterogeneous AI-enabled UAV systems while revealing design trade-offs that may not be apparent when these dimensions are considered independently.

Applying the framework across the surveyed literature reveals several recurring trends. Most existing research remains centered on communication and sensing missions, frequently paired with heavy stack-level investment in autonomous navigation and control capabilities. At the architectural level, AI is concentrated primarily within perception, communication optimization, and control functions, whereas higher-level concerns such as governance, ethics, cybersecurity, and societal acceptance

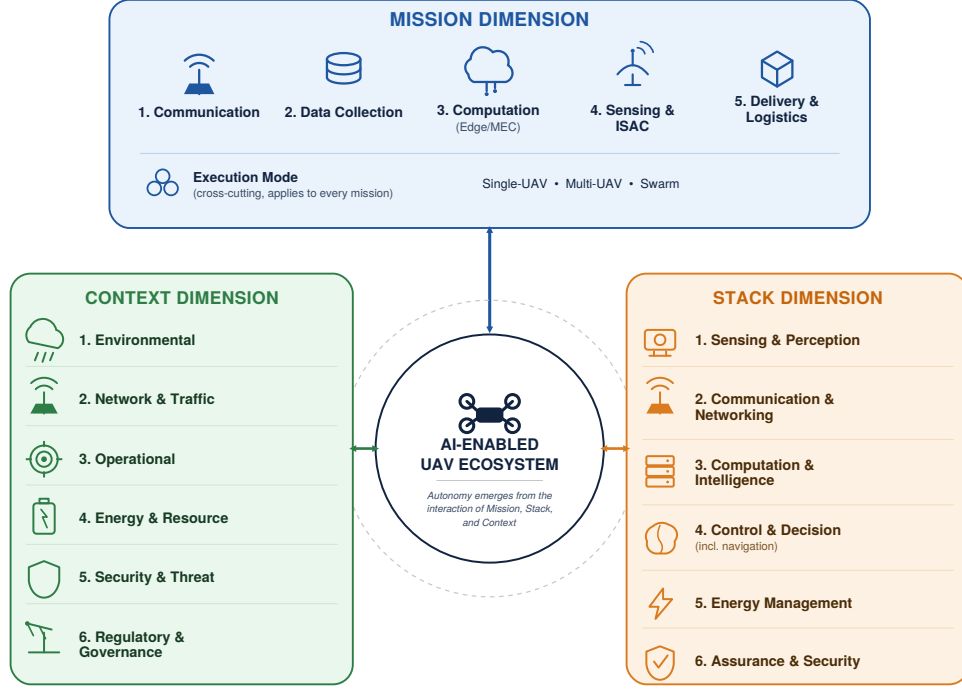


Fig. 1 Mission–Stack–Context (MSC) framework for AI-enabled UAV ecosystems.

receive comparatively less attention despite their growing importance for real-world deployment (Section 8).

Although **MSC** captures what a **UAV** ecosystem is designed to accomplish, how it is implemented, and the conditions under which it operates, it does not distinguish the extent to which **AI** drives system behavior. Two ecosystems with similar mission profiles, architectures, and deployment contexts may rely on fundamentally different levels of autonomy and intelligent decision making. Characterizing this dimension requires an additional perspective, motivating the **AIMM-UAV** introduced in the next section.

5 AI Integration Maturity Model for UAVs (AIMM-UAV)

The **MSC** framework describes **UAV** ecosystems in terms of their missions, technological architectures, and deployment contexts, but systems occupying similar positions in this design space may still differ substantially in the role played by **AI**: some platforms rely on predefined rules or limited automation, while others continuously perceive, learn, adapt, and make decisions with minimal human intervention. The proposed **AIMM-UAV** captures this missing dimension, characterizing the progressive transition

from manual operation to fully autonomous, adaptive, ecosystem-aware intelligence – not by focusing on application domains or hardware, but by treating intelligence as a system-wide property emerging from the interaction of sensing, communication, computation, control, and governance. Used together, [MSC](#) and [AIMM-UAV](#) are complementary: [MSC](#) explains what a system is designed to accomplish and under which conditions, while [AIMM-UAV](#) captures how deeply intelligent capabilities are integrated into that system. As a result, maturity depends not only on the sophistication of individual [AI](#) techniques but on the extent to which they shape system behavior, operational decision making, and autonomous adaptation.

5.1 Design Principles

The framework is built upon five complementary design principles:

- **Progressive Autonomy:** Maturity levels reflect the gradual transition from human-controlled operation to increasingly autonomous and adaptive behavior.
- **Distributed Intelligence:** Intelligence is often distributed across onboard platforms, edge infrastructure, cloud services, and cooperating [UAVs](#). Higher maturity levels therefore represent increasing levels of collaborative and decentralized intelligence.
- **Learning and Adaptation:** Maturity goes beyond automation to the ability to learn from data, adapt to changing environments, and continuously improve operational performance.
- **Human–AI Collaboration:** Human operators remain integral to many [UAV](#) ecosystems. This principle captures how responsibility progressively shifts from human supervision toward autonomous decision making.
- **Governance and Trustworthiness:** Increasing autonomy must be accompanied by stronger guarantees for safety, security, explainability, accountability, and regulatory compliance.

Together, these principles define six maturity levels spanning the evolution from manual operation to ecosystem-wide intelligence. Rather than serving as rigid categories, the levels provide a common reference for comparing heterogeneous [UAV](#) systems and understanding how [AI](#) capabilities evolve across different application domains.

5.2 AIMM-UAV Levels

The proposed [AIMM-UAV](#) distinguishes six levels of [AI](#) integration that reflect the evolution of [UAV](#) ecosystems from fully human-operated platforms to collaborative, ecosystem-scale autonomous systems. Progression through these levels is characterized by increasing decision-making autonomy, learning capability, system coordination, and operational independence.

5.2.1 AIMM-0: Manual Operation

Manual operation represents the starting point of the maturity model. At this level, all mission planning, navigation, sensing interpretation, and operational decisions are

performed by human operators, while the UAV serves primarily as a remotely piloted platform with little or no onboard intelligence.

Early UAV architectures reviewed in [76] exemplify this platform-centric paradigm, where operators remain responsible for mission execution, navigation adjustments, and contingency management. Similarly, the survey by Shakhathreh et al. [73] describes many practical deployments in which autonomy is limited and system behavior is largely predetermined. Within the MSC framework, missions, technological capabilities, and contextual conditions remain relatively static, resulting in limited adaptability to changing operational environments.

5.2.2 AIMM-1: Rule-Based Automation

The first step toward autonomy introduces predefined control logic that automates routine operational tasks. Functions such as waypoint navigation, geofencing, return-to-home procedures, mission scripting, and basic obstacle avoidance can be executed without continuous human intervention. Nevertheless, system behavior remains deterministic because every action follows rules specified in advance.

Although these capabilities improve operational efficiency, they do not provide genuine adaptability. Unexpected situations still require human intervention, and mission execution remains constrained by predefined assumptions regarding the environment and operating conditions. Similar forms of deterministic automation are discussed in [31, 76].

5.2.3 AIMM-2: Assisted Intelligence

A significant transition occurs at AIMM-2, where AI begins assisting rather than replacing human decision making. Learning algorithms support perception, object detection, target recognition, trajectory optimization, communication management, and resource allocation, while human operators retain authority over mission-critical decisions.

This level reflects the growing use of data-driven decision support rather than fully autonomous control. Won et al. [83], for example, review numerous machine-learning approaches for UAV placement, trajectory optimization, and resource allocation that remain embedded within centrally managed optimization frameworks. Likewise, the survey by Bithas et al. [84] highlights the application of learning techniques to link adaptation, coverage enhancement, and scheduling optimization. These methods improve operational performance but continue to rely on human supervision and relatively fixed operational policies.

5.2.4 AIMM-3: Supervised Autonomy

AIMM-3 marks the point at which autonomous decision making becomes a fundamental system capability. Rather than simply assisting operators, the UAV independently performs navigation, path planning, obstacle avoidance, and mission adaptation while remaining under human supervision. Operators primarily monitor system behavior and intervene only when necessary.

RL has become one of the defining technologies at this maturity level because it enables sequential decision making under dynamic operating conditions. Chen et al. [85] provide a comprehensive overview of RL techniques for autonomous UAV systems. Representative examples include the adaptive computation offloading framework proposed by Li et al. [86] and the joint trajectory planning and transmission scheduling approach developed by Luo et al. [62]. Although these methods enable real-time adaptation, they are generally optimized for specific missions and environments, limiting their ability to generalize across substantially different deployment scenarios.

5.2.5 AIMM-4: Collaborative Autonomy

The defining characteristic of AIMM-4 is that intelligence extends beyond individual platforms to coordinated groups of autonomous agents. Execution mode alone does not determine this level. For instance, a rule-based multi-UAV formation remains at AIMM-1, while AIMM-4 requires the coordination itself to be intelligent and adaptive. Multiple UAVs cooperate by exchanging information, coordinating actions, and collectively adapting their behavior to achieve shared mission objectives. Distributed intelligence, swarm coordination, federated learning, and collaborative decision making become essential capabilities.

Recent work demonstrates how multi-agent reinforcement learning and distributed optimization can support scalable cooperation and adaptive task allocation. Wu et al. [6] present a swarm redeployment strategy based on collaborative intelligence, while Hou et al. [36] develop a cooperative target-search framework in which collective behavior emerges from interactions among autonomous agents. These approaches substantially improve mission effectiveness and resilience but also introduce new challenges related to communication overhead, synchronization, and distributed trust.

5.2.6 AIMM-5: Ecosystem Intelligence

The highest maturity level extends intelligence beyond individual platforms and swarms to encompass the entire operational ecosystem. Autonomous UAVs, communication infrastructures, edge and cloud platforms, digital twins, IoT systems, and human stakeholders function as interconnected components of a continuously adapting intelligent environment. Decision making is no longer confined to individual agents but emerges through coordinated interactions across the ecosystem.

Technologies such as digital twins, edge intelligence, and distributed learning enable continuous adaptation using real-time environmental information and shared knowledge. This ecosystem-wide perspective supports mission-level optimization that transcends the objectives of individual platforms. At the same time, increasing autonomy places greater emphasis on governance, requiring mechanisms that ensure safety, accountability, explainability, trustworthiness, and regulatory compliance [16, 17].

Figure 2 summarizes the progression of AI integration across the six maturity levels. As intelligence evolves from manual operation to ecosystem-wide autonomy, decision making becomes progressively more adaptive, collaborative, and distributed, reflecting the increasing complexity of future AI-enabled UAV ecosystems.

MATURITY LEVEL	AIMM-0	AIMM-1	AIMM-2	AIMM-3	AIMM-4	AIMM-5
LEVEL NAME	Manual Operation	Rule-Based Automation	Assisted Intelligence	Supervised Autonomy	Collaborative Autonomy	Ecosystem Intelligence
DEFINITION	All operations are performed by human operators without AI capabilities.	Predefined rules and automation support basic functions with deterministic behavior.	AI provides situational awareness and recommendations to support human decisions.	UAV performs mission tasks autonomously within defined boundaries under human supervision.	Multiple UAVs coordinate and collaborate to achieve mission objectives with limited human intervention.	Fully integrated UAV ecosystems with adaptive, self-optimizing intelligence across domains.
KEY CAPABILITIES	- Manual piloting - Human perception - Human decision making - No onboard intelligence	- Waypoint navigation - Altitude hold, geofencing - Return-to-home - Event-triggered actions	- AI-based perception - Object detection/recognition - Anomaly detection - Decision support	- Autonomous navigation - Obstacle avoidance - Mission adaptation - Health monitoring	- Multi-UAV coordination - Distributed perception - Task allocation - Edge/federated learning	- Cross-domain collaboration - Continuous learning - Self-optimization - Resilient, adaptive, scalable
HUMAN ROLE	Full Control Operator handles all tasks.	Operator in Control Operator plans and monitors.	Operator Decides AI assists; human makes final decisions.	Supervisor Monitors and intervenes if needed.	Mission Manager Sets objectives and monitors mission.	Strategic Oversight Human defines goals and constraints.
EXAMPLES	RC drones, basic hobbyist UAVs	GPS-based UAVs, automated flight modes	AI-assisted mapping, inspection, surveillance UAVs	BVLOS operations, autonomous inspection UAVs	Swarm operations, disaster response, large-area monitoring	Smart city ecosystems, UAV-UGV integration, autonomous logistics
AUTONOMY	○ None	● Low	● Low – Moderate	● Moderate – High	● High	● Very High
LEARNING CAPABILITY	○ None	○ None	● Basic	● Moderate	● High	● Very High (Continuous)
COORDINATION	○ None	○ None	● Single UAV	● Single Platform	● Multi-UAV	● Ecosystem-Wide
GOVERNANCE REQUIREMENTS	○ Low	● Low	● Moderate	● High	● Very High	● Extremely High
 From Human-Controlled Operations → To Intelligent, Collaborative UAV Ecosystems 						

Fig. 2 Progression of AI integration across the AIMM-UAV maturity levels.

5.3 Mapping AIMM-UAV to the MSC Framework

Building on this distinction between what a system does and how deeply intelligence shapes it, Figure 3 illustrates how the relationships among Mission, Stack, and Context evolve across the maturity levels. At AIMM-0 and AIMM-1, objectives, technological functions, and operating assumptions are largely predefined, leaving limited scope for adaptation. AIMM-2 introduces data-driven assistance, while AIMM-3 allows the system to make autonomous decisions within predefined supervisory boundaries. At AIMM-4 and AIMM-5, intelligence becomes more distributed, linking multiple platforms, infrastructures, and stakeholders through collaborative and ecosystem-wide decision making.

This mapping also shows that maturity cannot be assessed solely through the sophistication of individual algorithms. Moving toward higher levels requires stronger integration among sensing, communication, computation, control, coordination, and governance functions. A technically advanced learning method may therefore remain at a relatively modest maturity level if it operates in isolation or has limited influence on mission-level decisions. Conversely, ecosystem intelligence depends on the ability to combine intelligent components into a coherent, adaptive, and trustworthy operational system.

6 Energy–Autonomy Budget (EAB) Framework

The MSC and AIMM-UAV frameworks describe how intelligent UAV ecosystems are organized and how autonomy evolves across levels of AI integration. A remaining question is whether the desired level of autonomy can be sustained in practice, since

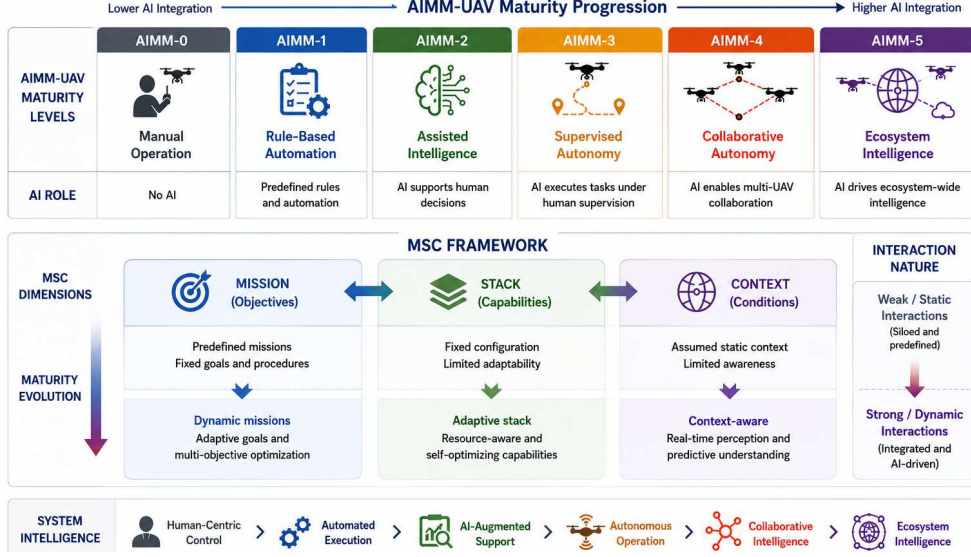


Fig. 3 Integration of the AIMM-UAV and MSC frameworks. Increasing AI maturity transforms the interactions among mission objectives, stack capabilities, and contextual conditions from static and predefined relationships toward adaptive, collaborative, and ecosystem-wide intelligence.

regardless of algorithmic sophistication, autonomous operation ultimately depends on finite energy reserves and the computation, communication, and sensing resources that consume them. The proposed EAB addresses this by treating autonomy as a resource-dependent capability rather than a purely algorithmic one: flight, sensing, computation, and communication continuously compete for the same onboard resources, and mission endurance is significantly influenced by processing workloads, sensing requirements, communication activity, and AI inference in addition to propulsion [78, 79, 87]. As autonomous functionality becomes more sophisticated, these competing demands grow increasingly intertwined, creating fundamental trade-offs between operational endurance, mission performance, and intelligent decision making.

EAB emphasizes the strong interdependence of energy, computation, and communication rather than treating them independently. Han et al. [14], for example, propose a cloud-edge-terminal command architecture that jointly allocates computational, communication, and energy resources across distributed UAV systems, while recent work on energy-aware task offloading and intelligent UAV architectures [80, 88] shows that improvements in sensing fidelity, onboard intelligence, and collaborative operation inevitably increase both computational workload and communication demand. The resulting perspective views autonomy as a dynamic balance between available resources and the intelligent functions that consume them.

6.1 Computational Load as a Driver of Autonomy

Modern autonomous UAVs highly depend on computationally intensive AI workloads. Perception, object detection, simultaneous localization and mapping (SLAM), trajectory planning, anomaly detection, and autonomous navigation all require continuous execution of machine-learning models and real-time inference. As systems progress toward higher AIMM-UAV levels, these workloads demand increasingly capable onboard computing platforms, including embedded GPUs, dedicated AI accelerators, edge-computing modules, and specialized low-power hardware [87].

Recent advances demonstrate that higher computational capability does not necessarily imply higher energy consumption. Lightweight neural networks, model compression, quantization techniques, and hardware-aware optimization enable sophisticated AI functions to execute efficiently on resource-constrained platforms while maintaining acceptable inference accuracy [89, 90]. These developments illustrate that computational capability is itself a component of the autonomy budget: advanced autonomy can only be sustained if the required processing workload remains compatible with the available energy resources [78, 79].

6.2 Communication Load and Distributed Intelligence

As autonomy becomes highly distributed, communication evolves from a supporting function into a core system resource. Cloud offloading, edge intelligence, swarm coordination, digital twin synchronization, and collaborative sensing all depend on continuous information exchange among aerial platforms and supporting infrastructures. Emerging communication technologies, particularly 5G and future 6G networks, are therefore becoming fundamental enablers of intelligent UAV ecosystems [8].

The additional connectivity, however, introduces its own resource demands. Every transmitted message consumes bandwidth, communication energy, and onboard processing capacity. These costs become especially significant in collaborative missions, where multiple UAVs must frequently synchronize decisions and exchange environmental information. Ai et al. [91] demonstrate that communication management is therefore central to balancing collaborative intelligence against mission endurance.

Within the EAB framework, communication is viewed as both an enabler of autonomy and a consumer of limited resources. Increasing intelligence often requires greater communication activity, making efficient information exchange an essential component of sustainable autonomous operation.

6.3 Energy Coupling and Resource Allocation

The central idea behind EAB is that energy is not consumed by propulsion alone but shared among all functions supporting autonomous operation. From this perspective, the onboard energy budget can be divided into four principal components:

1. Propulsion and flight control;
2. Sensing and payload operation;
3. Computational processing;
4. Communication and networking.

These four domains can be conceptually represented as:

$$E_{\text{total}} = E_{\text{flight}} + E_{\text{sense}} + E_{\text{comp}} + E_{\text{comm}}, \quad (1)$$

where E_{flight} , E_{sense} , E_{comp} , and E_{comm} denote the energy allocated to propulsion, sensing, computation, and communication, respectively. This decomposition emphasizes that every additional autonomous capability ultimately draws energy from the same finite onboard reserve.

Although propulsion remains the dominant source of energy consumption for most UAVs, the contribution of sensing, computation, and communication increases steadily as autonomy becomes more sophisticated. Traspadini et al. [78] highlight the growing impact of onboard processing and communication on total energy consumption, while Zhang et al. [79] identify the joint management of sensing, communication, and computing resources as a central challenge for intelligent UAV systems. The trend becomes even more pronounced in collaborative and multi-agent deployments that rely on continuous perception, learning, and coordination.

Resource allocation therefore becomes an exercise in balancing competing objectives. Increasing sensing frequency, running larger learning models, or exchanging additional information can improve mission performance but inevitably reduces the energy available for sustained flight. Conversely, extending mission endurance may require simplifying onboard intelligence, reducing sensing activity, or limiting communication. The EAB framework captures this fundamental trade-off between autonomy and endurance by emphasizing that intelligent functionality must be evaluated together with the resources required to sustain it.

Battery state estimation, remaining flight-time prediction, and adaptive energy-management strategies are consequently becoming integral components of intelligent UAV systems [92, 93].

6.4 Integrating EAB with MSC and AIMM-UAV

Figure 4 illustrates how MSC, AIMM-UAV, and EAB combine into a unified design methodology. The process begins by identifying mission objectives, technological capabilities, and operational constraints using MSC; the corresponding level of autonomy is then assessed through AIMM-UAV, providing an estimate of the intelligent functionality required to accomplish the mission; and EAB finally evaluates whether the available resource budget – energy, computation, sensing, and communication – is sufficient to sustain that level of autonomy throughout mission execution.

If the available resources prove insufficient, the designer can iteratively refine the system by adjusting mission objectives, simplifying AI models, modifying communication strategies, introducing edge-computing support, or improving onboard hardware capabilities. Sustainable autonomy therefore emerges not from maximizing intelligence alone, but from balancing mission requirements, technological capabilities, contextual constraints, and resource availability within a single integrated design process.

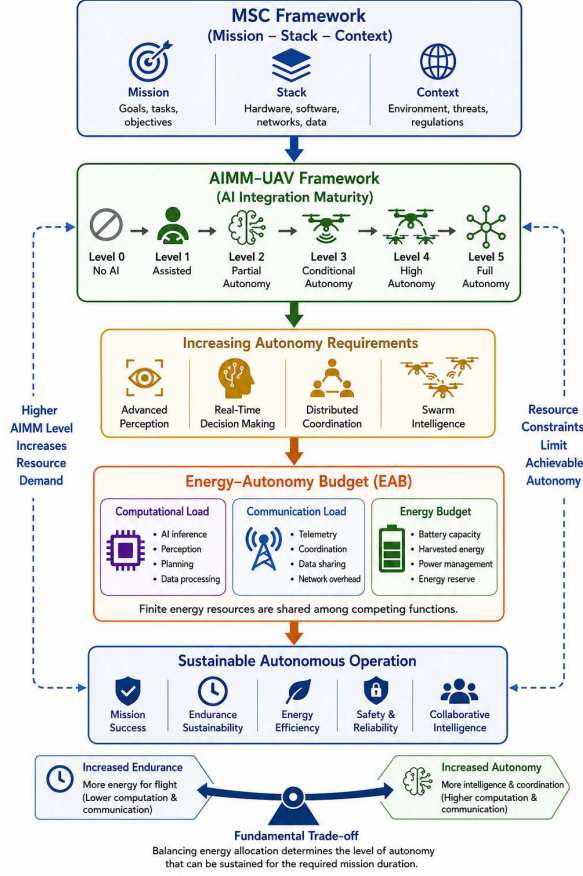


Fig. 4 Relationship among MSC, AIMM-UAV, and EAB within AI-enabled UAV ecosystems.

7 Cross-Sector Synthesis of AI-Enabled UAV Ecosystems

The surveyed literature demonstrates that intelligent UAV systems are shaped by the combined influence of mission requirements, technological capabilities, and operational context. None of these dimensions can adequately explain system behavior in isolation. Mission objectives determine the sensing, communication, and decision-making capabilities that are required, while the available technology stack constrains how these functions can be realized. Environmental conditions, regulations, and infrastructure availability further influence whether a proposed solution can be deployed effectively in practice.

Mission requirements are often the primary source of architectural diversity. Applications such as surveillance, inspection, mapping, logistics, healthcare delivery, humanitarian response, and environmental monitoring impose markedly different demands in terms of sensing modalities, communication range, navigation precision,

payload capacity, and response latency. As mission complexity increases, systems generally require more advanced perception, onboard intelligence, and autonomous decision-making capabilities. This trend is reflected across a wide range of application domains, including medical delivery [10], humanitarian operations [11, 82], deep-learning-based surveillance [7], and environmental monitoring [12]. Although these applications address different operational objectives, they consistently demonstrate how mission characteristics drive the selection of sensing, communication, and autonomy mechanisms.

A similar evolution can be observed within the technology stack. Remotely piloted platforms typically rely on relatively simple sensing and communication infrastructures, whereas more autonomous systems integrate edge computing, artificial intelligence, computer vision, digital twins, and cloud-edge collaboration. Despite this rapid technological progress, many stack components continue to evolve independently. As a result, perception, planning, communication, and cybersecurity are frequently optimized separately rather than as tightly integrated elements of a single intelligent ecosystem [13].

Operational context introduces another layer of complexity. Factors such as urban environments, indoor operation, remote regions, or disaster-affected areas directly influence communication reliability, navigation accuracy, sensing quality, and energy consumption. Humanitarian missions, for example, must cope with rapidly changing environments and damaged infrastructure, while environmental monitoring often takes place in remote areas where connectivity and computational resources are limited [11, 12, 82]. Regulatory frameworks and cybersecurity requirements further shape deployment decisions and vary significantly across jurisdictions and application domains [13]. Consequently, many published solutions perform well under carefully defined operating conditions but provide limited evidence of their robustness in substantially different environments.

One recurring observation throughout the literature is the imbalance between mission ambition and technological maturity. Numerous studies envision highly autonomous missions while relying on communication infrastructures, sensing capabilities, or coordination mechanisms that remain insufficiently validated for operational deployment. Humanitarian and disaster-response systems, for instance, often assume reliable autonomous coordination despite challenging communication conditions and complex stakeholder interactions [11, 82]. Conversely, other studies demonstrate highly sophisticated technological capabilities but target relatively narrow mission objectives. Deep-learning-based perception systems achieve remarkable object-detection performance [7], while advanced environmental monitoring platforms provide accurate sensing and mapping capabilities [12]; however, these contributions are generally optimized for specific tasks rather than broader ecosystem-level autonomy. This contrast suggests that much of the current literature continues to advance individual disciplines faster than fully integrated autonomous ecosystems.

Several broader challenges also emerge consistently across application domains. Interoperability among heterogeneous platforms, communication technologies, sensors, and software frameworks remains limited despite significant progress in networking and edge-computing architectures [8, 9, 14, 15]. Security, privacy, trustworthiness, and

system dependability are strongly recognized as critical requirements, yet they are still commonly addressed as separate research topics rather than integral design principles [13, 81, 82]. In addition, many studies emphasize the performance of individual components under controlled conditions while giving comparatively less attention to scalability, resilience, maintainability, and regulatory compliance. The lack of standardized evaluation methodologies further complicates objective comparison across application domains, although initiatives such as UAVBench represent an important step toward more consistent benchmarking [94].

The classifications presented in Table 4 further illustrate that autonomy maturity depends on considerably more than the sophistication of individual AI algorithms. Structured applications such as precision agriculture typically remain within AIMM-UAV levels 1–2 because operations follow predefined flight plans and AI primarily supports data collection and analysis under human supervision. Healthcare logistics and public-safety missions generally require higher levels of autonomy (AIMM 2–4), reflecting the need for adaptive navigation, real-time decision making, and operation under dynamic conditions while still maintaining human oversight for safety-critical tasks. Collaborative swarm applications occupy the highest maturity levels because mission success depends on distributed intelligence, coordinated adaptation, and continuous cooperation among multiple autonomous agents. Achieving these capabilities takes more than advanced learning algorithms; it takes stronger integration of communication, computation, coordination, and governance across the entire ecosystem.

Taken together, these observations reinforce the motivation for the proposed frameworks. The MSC framework provides a structured way to analyze mission requirements, technological capabilities, and operational context, while AIMM-UAV characterizes how intelligence is embedded within those dimensions. The proposed EAB complements this perspective by evaluating whether the desired level of autonomy can be sustained using the available computational, communication, and energy resources. Viewed collectively, the three frameworks provide a unified perspective for comparing heterogeneous UAV systems, identifying research gaps, and guiding the design of future intelligent aerial ecosystems.

8 Governance and Trustworthy AI for UAV Ecosystems

Greater autonomy brings greater responsibility. As UAV ecosystems evolve from remotely piloted platforms to intelligent, collaborative systems, technical performance alone is no longer sufficient. Safe and trustworthy deployment also depends on effective governance that addresses safety, security, privacy, accountability, transparency, and regulatory compliance. Rather than being viewed as an external constraint, governance should be considered an integral component of autonomous UAV ecosystems, enabling intelligent systems to operate safely and gain the confidence of operators, regulators, and society.

Table 4 Cross-sector synthesis of AI-enabled UAV ecosystems using the MSC, AIMM-UAV, and EAB frameworks. L: Low, M: Medium, H: High, VH: Very High.

Sector	Primary Mission Objective	Mission	Stack	Context	AIMM	Key EAB Challenge
Agriculture	Crop monitoring, precision spraying, field assessment	M	M	L-M	2	Flight endurance and large-area coverage
Infrastructure Inspection	Asset monitoring, anomaly detection, maintenance support	M-H	H	M	2-3	High-resolution sensing and onboard processing
Environmental Monitoring	Data collection, mapping, ecological assessment	M	M	M-H	1-2	Long-duration operation in remote environments
Healthcare Logistics	Medical delivery, emergency support	H	H	H	2-3	Reliability, safety, and communication availability
Public Safety & Disaster Response	Search and rescue, situational awareness, emergency coordination	H	H	H	3-4	Real-time communication and mission adaptability
Communication Networks	Coverage extension, aerial relays, temporary base stations	H	H	M-H	3-4	Communication-computation-energy trade-offs
Collaborative Swarms	Distributed sensing, cooperative missions, collective autonomy	VH	VH	H	4-5	Scalable coordination and communication overhead

8.1 Trustworthy AI and Governance Challenges

The growing adoption of AI has made trustworthy system behavior a central design objective. Existing governance frameworks consistently emphasize transparency, explainability, robustness, accountability, human oversight, and security as essential principles for responsible AI deployment [16–18]. These principles are particularly critical in UAV applications because autonomous decisions can directly influence public safety, critical infrastructure, healthcare logistics, and emergency-response operations.

Explainability is especially important as AI assumes greater responsibility for navigation, target recognition, mission planning, and resource allocation. Operators, regulators, and other stakeholders must be able to understand the reasoning behind autonomous decisions, not merely the decisions themselves. This need becomes particularly evident in safety-critical applications such as healthcare delivery and disaster response, where incorrect decisions may have significant operational consequences [10, 11, 82]. Accordingly, recent studies advocate governance-by-design approaches in which transparency, accountability, and human oversight are incorporated throughout the system lifecycle rather than introduced after deployment [16–18].

Security presents a closely related challenge. Intelligent UAV ecosystems rely on interconnected sensing, communication, computing, and control infrastructures that are exposed to threats such as spoofing, jamming, adversarial attacks, data manipulation, and unauthorized access. Vulnerabilities may arise at multiple levels, ranging from onboard AI models and navigation systems to wireless communication links and cloud-edge infrastructures [13, 81]. Because autonomous platforms continuously cooperate and exchange information, security failures can propagate beyond individual vehicles and affect the operation of the broader ecosystem.

Table 5 Governance requirements across AIMM-UAV maturity levels.

AIMM Level	Primary Governance Focus
0	Operator responsibility and procedural compliance
1	Rule verification and deterministic behavior assurance
2	Human oversight and decision-support validation
3	Explainability, auditability, and supervisory control
4	Distributed accountability, trust management, and coordinated decision making
5	Ecosystem governance, assurance, and regulatory compliance

Governance requirements also vary according to the mission and operating environment. Healthcare logistics place strong emphasis on safety, privacy, and reliability, whereas humanitarian operations require transparent and accountable decision making under highly uncertain conditions [10, 11, 82]. Communication-oriented applications introduce additional concerns related to network resilience and spectrum management, while surveillance missions raise important questions regarding privacy and data protection. Effective governance therefore depends on the mission objectives, technological capabilities, and operational context in which the system is deployed, not on the level of autonomy alone.

8.2 Governance Across AIMM-UAV Maturity Levels

Governance evolves alongside autonomy. At the lower AIMM-UAV levels, where systems remain manually operated or primarily rule-based, governance focuses on operator responsibility, procedural compliance, and verification of deterministic behavior. Human operators retain direct responsibility for mission execution, making accountability relatively straightforward.

As systems transition toward assisted intelligence and supervised autonomy, governance must address a broader range of concerns. AI models influence operational decisions, making explainability, auditability, continuous monitoring, and meaningful human oversight essential. Governance at these levels seeks to ensure that operators can understand, validate, and intervene in autonomous behaviors whenever necessary.

The challenges become more complex once autonomy extends beyond individual platforms. Collaborative swarms, edge-cloud integration, and digital-twin-enabled ecosystems distribute decision making across multiple autonomous agents and supporting infrastructures. Under these conditions, responsibility is no longer confined to a single operator or platform but shared among UAVs, communication networks, computing resources, and human stakeholders. Traditional governance models based on centralized control therefore become progressively more difficult to apply.

This evolution is reflected in the AIMM-UAV maturity model, where governance expands from supervising individual platforms to coordinating entire intelligent ecosystems. Table 5 summarizes the primary governance priorities associated with each maturity level.

The transition toward highly autonomous UAV ecosystems therefore requires governance mechanisms to evolve alongside technological capabilities. Emerging work

on dependable autonomy, trustworthy [AI](#), standardized evaluation, and certification methodologies provides an important foundation for this transition [15, 17, 81, 94]. However, large-scale deployment will ultimately depend on closer alignment between technological innovation, assurance and certification processes, regulatory frameworks, and societal expectations.

Viewed from this perspective, governance is not simply another layer of the [UAV](#) architecture. It is the mechanism that enables autonomous systems to remain safe, trustworthy, and accountable as intelligence expands from individual platforms to interconnected ecosystem-scale operations.

8.3 Future Research Directions

Recent advances in [AI](#), communication networks, robotics, and autonomous systems have significantly expanded the capabilities of [UAV](#) platforms, yet achieving fully intelligent aerial ecosystems remains an open challenge. What the [MSC](#), [AIMM-UAV](#), and [EAB](#) frameworks developed in this paper make clear is that future progress hinges less on advances in individual technologies than on their ability to operate as integrated, adaptive, and sustainable ecosystems. The remainder of this subsection discusses the research directions expected to shape the next generation of intelligent [UAV](#) systems.

8.3.1 Intelligent and Adaptive UAV Ecosystems

[AI](#) is highly embedded in perception, navigation, communication management, resource allocation, and mission planning, yet most existing solutions remain highly specialized, achieving strong performance only within the environments or datasets for which they were designed [15, 83, 85]. Generalizing autonomous behavior across missions and operating conditions therefore remains a major open challenge. Emerging technologies – including foundation models, multimodal learning, generative [AI](#), and autonomous agents – offer new opportunities for systems that reason under uncertainty and adapt continuously without sacrificing safety or reliability, although reinforcement learning’s promising simulation results have yet to translate into consistently reliable real-world performance.

Viewed through the [MSC](#) framework, future systems should move beyond optimizing isolated tasks toward jointly adapting mission objectives, technological capabilities, and contextual constraints, dynamically reconfiguring sensing, communication, and decision-making strategies as operating conditions evolve.

8.3.2 Resource-Aware and Sustainable Autonomy

Increasing autonomy inevitably increases resource demand, as more sophisticated perception, collaborative decision making, and continuous environmental awareness compete for limited onboard energy, computation, and communication. Yet many existing studies continue to evaluate autonomy primarily through task performance while assuming abundant computational power, reliable communication, or sufficient battery capacity – conditions rarely met in practical deployments. Recent research therefore recognizes that energy, communication, and computation must be managed

jointly rather than optimized independently [14, 78, 79], a need that grows more pressing as systems progress toward higher **AIMM-UAV** maturity levels.

Future work is therefore likely to focus on adaptive workload management, energy-aware inference, intelligent task offloading, and resource-efficient multi-agent coordination, while progress in battery technologies, wireless charging, and energy harvesting further extends mission endurance [80, 88]. More broadly, sustainable autonomy will require treating energy, computation, and communication as a unified resource budget rather than as separate optimization problems.

8.3.3 Trustworthy and Governable AI

Building autonomous systems also raises fundamental questions of trust, accountability, and governance: future **UAV** ecosystems must satisfy demanding requirements for explainability, transparency, cybersecurity, privacy, and regulatory compliance while maintaining high operational performance. Recent governance initiatives consistently emphasize human oversight, accountability, and explainability as prerequisites for responsible autonomous systems [16–18], yet many current **UAV** solutions continue to prioritize performance metrics while offering limited support for transparent decision making, formal verification, or post-mission auditing – shortcomings that become especially significant in healthcare, emergency response, and critical infrastructure deployments.

Security introduces a related challenge, as growing reliance on edge computing, cloud services, and collaborative intelligence expands the attack surface and creates new vulnerabilities throughout the ecosystem [13, 81]. Standardized evaluation and benchmarking initiatives such as UAVBench will play a critical role in enabling objective comparison and certification of autonomous capabilities across deployment scenarios [94].

8.3.4 From Platform-Centric to Ecosystem-Centric UAV Systems

Perhaps the most profound transformation lies in the shift from individual autonomous platforms to intelligent aerial ecosystems. Research has historically concentrated on improving single-**UAV** capabilities, and although attention has expanded toward collaborative swarms, edge computing, digital twins, and distributed intelligence [8, 14, 77], these advances are still frequently developed in isolation rather than as components of a unified ecosystem. The **AIMM-UAV** framework suggests that future autonomy will instead emerge through cooperation among multiple platforms, communication infrastructures, cloud-edge resources, digital twins, **IoT** systems, and human stakeholders, building on recent advances in multi-agent reinforcement learning for large-scale coordination and adaptive task allocation [6, 36].

Realizing ecosystem-level autonomy will require addressing challenges beyond artificial intelligence itself, including interoperability, distributed decision making, trust management, data governance, resilience, and certification, with federated learning, multi-agent reinforcement learning, and digital-twin-enabled decision support likely to become central building blocks. Ultimately, this transition requires systems-integration and governance progress alongside technological progress, and the **MSC**, **AIMM-UAV**,

and [EAB](#) frameworks introduced in this paper are intended to help identify the advances it demands.

9 Conclusion

This review examined how [AI](#)-enabled [UAV](#) systems are evolving from isolated aerial platforms into connected and increasingly autonomous ecosystems. Across the surveyed literature, autonomy emerges not from [AI](#) alone but from the interaction of mission requirements, technological capabilities, operating conditions, and finite resource availability.

Three complementary frameworks were developed to organize this landscape. The [MSC](#) framework links mission objectives with technology-stack capabilities and contextual constraints. The [AIMM-UAV](#) framework describes how the role of intelligence progresses from manual operation and deterministic automation to collaborative and ecosystem-level autonomy. The [EAB](#) framework adds a resource perspective by examining whether a desired level of autonomy can be sustained under practical energy, computation, sensing, and communication constraints.

The cross-sector analysis revealed a recurring imbalance between ambitious mission concepts and the maturity of the technologies needed to support them. Higher autonomy typically demands stronger contextual awareness, tighter coordination among system components, and greater computational and communication capacity. At the same time, many proposed solutions remain difficult to transfer beyond narrowly defined scenarios. Interoperability, scalability, cybersecurity, governance, assurance, and resource sustainability therefore remain central obstacles to large-scale deployment.

Future progress will depend on bringing together advances that are still often developed separately. Artificial intelligence, edge computing, communication networks, digital twins, autonomous control, and multi-agent coordination must be integrated with comparable progress in standardization, certification, trustworthy system design, and human-[AI](#) collaboration. The transition toward intelligent aerial ecosystems is therefore as much a systems-integration and governance challenge as it is an algorithmic one.

[MSC](#), [AIMM-UAV](#), and [EAB](#) approach the same ecosystems from three angles – structural, autonomy, and resource-sustainability – and read together, they let designers compare existing systems, spot mismatches between mission ambition and deployment readiness, and steer the design of future [UAV](#) ecosystems that are adaptive, trustworthy, and sustainable.

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References

- [1] Hashima, S., Gendia, A., Hatano, K., Muta, O., Nada, M.S., Mohamed, E.M.: Next-gen uav-satellite communications: Ai innovations and future prospects. *IEEE Open Journal of Vehicular Technology* (2025)
- [2] Alzoubi, Y.I., Topcu, A.E., Elbasi, E.: A systematic review and evaluation of sustainable ai algorithms and techniques in healthcare. *IEEE Access* (2025)
- [3] Elbasi, E., Mostafa, N., Zaki, C., AlArnaout, Z., Topcu, A.E., Saker, L.: Optimizing agricultural data analysis techniques through ai-powered decision-making processes. *Applied Sciences* **14**(17), 8018 (2024)
- [4] Shukla, P., Shukla, S., Singh, A.K.: Trajectory-prediction techniques for unmanned aerial vehicles (uavs): A comprehensive survey. *IEEE Communications Surveys & Tutorials* **27**(3), 1867–1910 (2024)
- [5] Saha, D., Pattanayak, D., Mandal, P.S.: Surveillance of uneven surface with self-organizing unmanned aerial vehicles. *IEEE Transactions on Mobile Computing* **21**(4), 1449–1462 (2020)
- [6] Wu, Q., Geng, Z., Ren, Y., Feng, Q., Zhong, J.: Multi-uav redeployment optimization based on multi-agent deep reinforcement learning oriented to swarm performance restoration. *Sensors* **23**(23), 9484 (2023)
- [7] Anusha, N., Swapna, T.: Deep learning-based aerial object detection for unmanned aerial vehicles. In: *2023 International Conference on Sustainable Communication Networks and Application (ICSCNA)*, pp. 1241–1246 (2023). IEEE
- [8] Qasim, N.H., Jawad, A.M.: 5g-enabled uavs for energy-efficient opportunistic networking. *Heliyon* **10**(12) (2024)
- [9] Gu, X., Zhang, G.: A survey on uav-assisted wireless communications: Recent advances and future trends. *Computer Communications* **208**, 44–78 (2023)
- [10] Hanafiah, M.H.M., Al-Humairi, S.N.S., Taib, M.A.A.M., Jaharadak, A.A.: Analysis and optimization of care-purpose drone for medical-based applications. In: *2024 20th IEEE International Colloquium on Signal Processing & Its Applications (CSPA)*, pp. 184–189 (2024). IEEE

- [11] El-Sakka, A., Osman, A., Househ, M.: Revolutionizing disaster management: A scoping review of drone technology and informatics in humanitarian response. *Studies in Health Technology and Informatics* **329**, 1515–1519 (2025)
- [12] Robinson, J.M., Harrison, P.A., Mavoa, S., Breed, M.F.: Existing and emerging uses of drones in restoration ecology. *Methods in Ecology and Evolution* **13**(9), 1899–1911 (2022)
- [13] Alsadie, D.: Cybersecurity and artificial intelligence in unmanned aerial vehicles: Emerging challenges and advanced countermeasures. *IET Information Security* **2025**(1), 2046868 (2025)
- [14] Han, S., Wan, P., Lian, Z., Wang, M., Li, D., Fan, C.: Research on the construction and resource optimization of a uav command information system based on large language models. *Drones* **9**(9), 639 (2025)
- [15] Zhao, X., Chen, C., Xu, Z.: Towards intelligent, reliable uav networks: commentary on “advances in unmanned aerial systems: technologies, applications, and challenges”. *Complex Engineering Systems* **5**(3), (2025)
- [16] Roadmap, Artificial Intelligence: A human-centric approach to ai in aviation. European Aviation Safety Agency **1** (2020)
- [17] AI, NIST: Artificial intelligence risk management framework (ai rmf 1.0). URL: <https://nvlpubs.nist.gov/nistpubs/ai/nist.ai,100-1> (2023)
- [18] Estal Herrero, A., Apter, N., Hristozov, S.: A parametric comparison of jarus sora 2.0 and 2.5 ground risk models. *Engineering Proceedings* **90**(1), 47 (2025)
- [19] Sukhera, J.: Narrative reviews: flexible, rigorous, and practical. *Journal of graduate medical education* **14**(4), 414–417 (2022)
- [20] Turnbull, D., Chugh, R., Luck, J.: Systematic-narrative hybrid literature review: A strategy for integrating a concise methodology into a manuscript. *Social Sciences & Humanities Open* **7**(1), 100381 (2023)
- [21] Song, Z., Qin, X., Hao, Y., Hou, T., Wang, J., Sun, X.: A comprehensive survey on aerial mobile edge computing: Challenges, state-of-the-art, and future directions. *Computer Communications* **191**, 233–256 (2022)
- [22] Xia, X., Fattah, S.M.M., Babar, M.A.: A survey on uav-enabled edge computing: Resource management perspective. *ACM Computing Surveys* **56**(3), 1–36 (2023)
- [23] Bai, Y., Zhao, H., Zhang, X., Chang, Z., Jäntti, R., Yang, K.: Toward autonomous multi-uav wireless network: A survey of reinforcement learning-based approaches. *IEEE Communications Surveys & Tutorials* **25**(4), 3038–3067 (2023)
- [24] Peters, M.D., Godfrey, C., McInerney, P., Khalil, H., Larsen, P., Marnie, C.,

- Pollock, D., Tricco, A.C., Munn, Z.: Best practice guidance and reporting items for the development of scoping review protocols. *JB1 evidence synthesis* **20**(4), 953–968 (2022)
- [25] Pollock, D., Evans, C., Jia, R.M., Alexander, L., Pieper, D., Moraes, É.B., Peters, M.D., Tricco, A.C., Khalil, H., Godfrey, C.M., *et al.*: “how-to”: scoping review? *Journal of clinical epidemiology* **176**, 111572 (2024)
- [26] Cooper, C., Booth, A., Husk, K., Lovell, R., Frost, J., Schauburger, U., Britten, N., Garside, R.: A tailored approach: A model for literature searching in complex systematic reviews. *Journal of Information Science* **50**(4), 1030–1062 (2024)
- [27] Sarıkaya, B.S., Bahtiyar, Ş.: A survey on security of uav and deep reinforcement learning. *Ad Hoc Networks* **164**, 103642 (2024)
- [28] Tlili, F., Ayed, S., Fourati, L.C.: Advancing uav security with artificial intelligence: A comprehensive survey of techniques and future directions. *Internet of Things* **27**, 101281 (2024)
- [29] Smuha, N.A.: Regulation 2024/1689 of the eur. parl. & council of june 13, 2024 (eu artificial intelligence act). *International Legal Materials* **64**(5), 1234–1381 (2025)
- [30] Khalid, S., Singh, N.P.: Envisioning the future of unmanned aircraft systems traffic management: A 3-5 year roadmap. In: *Advanced Antenna Technologies for Aerial Platforms: From Design to Deployment*, pp. 235–298. IGI Global Scientific Publishing, Hershey, PA, USA (2025)
- [31] Mozaffari, M., Saad, W., Bennis, M., Nam, Y.-H., Debbah, M.: A tutorial on uavs for wireless networks: Applications, challenges, and open problems. *IEEE communications surveys & tutorials* **21**(3), 2334–2360 (2019)
- [32] Almuraqab, N.A.S., Ateeq, A., Manoj Kumar, M., Alfiras, M.: Public attitudes toward secure ai enabled drone delivery for public services in the uae. *Frontiers in Built Environment* **11**, 1640830 (2025)
- [33] Rahman, M., Sarkar, N.I., Lutui, R.: A survey on multi-uav path planning: Classification, algorithms, open research problems, and future directions. *Drones* **9**(4), 263 (2025)
- [34] Liu, J., Cui, J., Ye, M., Zhu, X., Tang, S.: Shooting condition insensitive unmanned aerial vehicle object detection. *Expert Systems with Applications* **246**, 123221 (2024)
- [35] Wu, W., Liu, A., Hu, J., Mo, Y., Xiang, S., Duan, P., Liang, Q.: Euavdet: An efficient and lightweight object detector for uav aerial images with an edge-based computing platform. *Drones* **8**(6), 261 (2024)

- [36] Hou, Y., Zhao, J., Zhang, R., Cheng, X., Yang, L.: Uav swarm cooperative target search: A multi-agent reinforcement learning approach. *IEEE Transactions on Intelligent Vehicles* **9**(1), 568–578 (2023)
- [37] Jarraya, I., Al-Batati, A., Kadri, M.B., Abdelkader, M., Ammar, A., Boulila, W., Koubaa, A.: GNSS-denied unmanned aerial vehicle navigation: analyzing computational complexity, sensor fusion, and localization methodologies. *Satellite Navigation* **6**(1), 9 (2025) <https://doi.org/10.1186/s43020-025-00162-z>
- [38] Frattolillo, F., Brunori, D., Iocchi, L.: Scalable and cooperative deep reinforcement learning approaches for multi-uav systems: A systematic review. *Drones* **7**(4), 236 (2023)
- [39] Yaacoub, J.-P., Noura, H., Salman, O., Chehab, A.: Security analysis of drones systems: Attacks, limitations, and recommendations. *Internet of Things* **11**, 100218 (2020)
- [40] Pal, O.K., Shovon, M.S.H., Mridha, M.F., Shin, J.: In-depth review of ai-enabled unmanned aerial vehicles: trends, vision, and challenges. *Discover Artificial Intelligence* **4**(1), 97 (2024)
- [41] Li, L., Zhu, L., Li, W.: Privacy-preserving federated learning for space–air–ground integrated networks: A bi-level reinforcement learning and adaptive transfer learning optimization framework. *Sensors* **25**(9), 2828 (2025)
- [42] Ahmad, T., Morel, A., Cheng, N., Palaniappan, K., Calyam, P., Sun, K., Pan, J.: Future uav/drone systems for intelligent active surveillance and monitoring. *ACM Computing Surveys* **58**(2), 1–37 (2025)
- [43] Mishra, D., Natalizio, E.: A survey on cellular-connected uavs: Design challenges, enabling 5g/b5g innovations, and experimental advancements. *Computer Networks* **182**, 107451 (2020)
- [44] Masaracchia, A., Li, Y., Nguyen, K.K., Yin, C., Khosravirad, S.R., Da Costa, D.B., Duong, T.Q.: Uav-enabled ultra-reliable low-latency communications for 6g: A comprehensive survey. *IEEE access* **9**, 137338–137352 (2021)
- [45] Yazid, Y., Ez-Zazi, I., Guerrero-González, A., El Oualkadi, A., Arioua, M.: Uav-enabled mobile edge-computing for iot based on ai: A comprehensive review. *Drones* **5**(4), 148 (2021)
- [46] Messaoudi, K., Oubbati, O.S., Rachedi, A., Lakas, A., Bendouma, T., Chaib, N.: A survey of uav-based data collection: Challenges, solutions and future perspectives. *Journal of network and computer applications* **216**, 103670 (2023)
- [47] Federal Aviation Administration: Beyond visual line of sight (BVLOS) fact sheet.

Technical report, U.S. Department of Transportation, Federal Aviation Administration (August 2025). Notice of Proposed Rulemaking (Part 108), published August 7, 2025. <https://www.faa.gov/newsroom/beyond-visual-line-sight-bvlos>

- [48] European Union Aviation Safety Agency: EASA artificial intelligence roadmap 1.0: A human-centric approach to AI in aviation. Technical report, European Union Aviation Safety Agency (February 2020). Version 1.0, published 7 February 2020. <https://www.easa.europa.eu/en/document-library/general-publications/easa-artificial-intelligence-roadmap-10>
- [49] European Union Aviation Safety Agency: EASA concept paper: Guidance for safety-related artificial intelligence applications, proposed issue 03. Technical report, European Union Aviation Safety Agency (June 2026). Published 3 June 2026, part of the EASA Artificial Intelligence Roadmap 2.0. <https://www.easa.europa.eu/en/document-library/general-publications>
- [50] Laghari, A.A., Jumani, A.K., Laghari, R.A., Nawaz, H.: Unmanned aerial vehicles: A review. *Cognitive robotics* **3**, 8–22 (2023)
- [51] Mu, J., Zhang, R., Cui, Y., Gao, N., Jing, X.: Uav meets integrated sensing and communication: Challenges and future directions. *IEEE Communications Magazine* **61**(5), 62–67 (2023)
- [52] Huang, H., Savkin, A.V.: Deployment of heterogeneous uav base stations for optimal quality of coverage. *IEEE Internet of Things Journal* **9**(17), 16429–16437 (2022)
- [53] Zhu, X., Zhai, L., Li, N., Li, Y., Yang, F.: Multi-objective deployment optimization of uavs for energy-efficient wireless coverage. *IEEE Transactions on Communications* **72**(6), 3587–3601 (2024)
- [54] El Debeiki, M., Al-Rubaye, S., Perrusquía, A., Conrad, C., Flores-Campos, J.A.: An advanced path planning and uav relay system: Enhancing connectivity in rural environments. *Future Internet* **16**(3), 89 (2024)
- [55] Hwang, R.-H., Lin, J.-Y., Lin, J.-Y., Lin, Y.-D.: Communication and computing offloading in 6g hotspot scenarios. In: 2025 IEEE International Conference on Communications Workshops (ICC Workshops), pp. 1525–1531 (2025). IEEE
- [56] Jiang, S., Huang, Z., Ji, Y.: Adaptive uav-assisted geographic routing with q-learning in vanet. *IEEE Communications Letters* **25**(4), 1358–1362 (2020)
- [57] Al-Hilo, A., Samir, M., Assi, C., Sharafeddine, S., Ebrahimi, D.: Uav-assisted content delivery in intelligent transportation systems-joint trajectory planning and cache management. *IEEE Transactions on Intelligent Transportation Systems* **22**(8), 5155–5167 (2020)

- [58] Joshi, P., Kalita, A., Gurusamy, M.: Reliable and efficient data collection in UAV-based IoT networks. *IEEE Communications Surveys & Tutorials* **28**, 2531–2571 (2026)
- [59] Gao, X., Zhu, X., Zhai, L.: Aoi-sensitive data collection in multi-uav-assisted wireless sensor networks. *IEEE Transactions on Wireless Communications* **22**(8), 5185–5197 (2023)
- [60] Hu, Y., Liu, Y., Kaushik, A., Masouros, C., Thompson, J.S.: Timely data collection for uav-based iot networks: A deep reinforcement learning approach. *IEEE Sensors Journal* **23**(11), 12295–12308 (2023)
- [61] Oubbati, O.S., Atiquzzaman, M., Lakas, A., Baz, A., Alhakami, H., Alhakami, W.: Multi-uav-enabled aoi-aware wpcn: A multi-agent reinforcement learning strategy. In: *IEEE INFOCOM 2021-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 1–6 (2021). IEEE
- [62] Luo, X., Chen, C., Zeng, C., Li, C., Xu, J., Gong, S.: Deep reinforcement learning for joint trajectory planning, transmission scheduling, and access control in uav-assisted wireless sensor networks. *Sensors* **23**(10), 4691 (2023)
- [63] Abbasi, A.B., Hadi, M.U.: Optimizing uav computation offloading via mec with deep deterministic policy gradient. *Transactions on Emerging Telecommunications Technologies* **35**(1), 4874 (2024)
- [64] Zhang, P., Wang, G., Chen, S., Yu, Y., Chen, L.: The application of mobile edge computing in the space-air-ground integrated network. *Journal of Intelligent Computing and Networking* **1**(1), 71–97 (2025)
- [65] Lyu, Z., Zhu, G., Xu, J.: Joint trajectory and beamforming design for uav-enabled integrated sensing and communication. In: *ICC 2022-IEEE International Conference on Communications*, pp. 1593–1598 (2022). IEEE
- [66] Moro, S., Linsalata, F., Manzoni, M., Magarini, M., Tebaldini, S.: Enhancing user localization with an integrated sensing and communication (isac) system: An experimental uav search-and-rescue use case. *Remote Sensing* **16**(16), 3031 (2024)
- [67] Benaya, A.M., Hassan, M.S., Ismail, M.H., Landolsi, T.: Aerial isac: A haps-assisted integrated sensing, communications and computing framework for enhanced coverage and security. *IEEE Transactions on Green Communications and Networking* (2025)
- [68] Mohamed, A., Mohamed, M.: Unmanned aerial vehicles in last-mile parcel delivery: A state-of-the-art review. *Drones* **9**(6), 413 (2025) <https://doi.org/10.3390/drones9060413>

- [69] Tarhan, F.A., Ure, N.K.: Genetic-algorithm-aided deep reinforcement learning for multi-agent drone delivery. *Drones* **8**(3), 71 (2024) <https://doi.org/10.3390/drones8030071>
- [70] Shu, X., Lin, A., Wen, X.: Energy-saving multi-agent deep reinforcement learning algorithm for drone routing problem. *Sensors* **24**(20), 6698 (2024) <https://doi.org/10.3390/s24206698>
- [71] Wang, D., Lian, B., Liu, Y., Gao, B.: A cooperative uav swarm localization algorithm based on probabilistic data association for visual measurement. *IEEE Sensors Journal* **22**(20), 19635–19644 (2022)
- [72] Bi, S., Li, K., Hu, S., Ni, W., Wang, C., Wang, X.: Detection and mitigation of position spoofing attacks on cooperative uav swarm formations. *IEEE Transactions on Information Forensics and Security* **19**, 1883–1895 (2023)
- [73] Shakhathreh, H., Sawalmeh, A.H., Al-Fuqaha, A., Dou, Z., Almaita, E., Khalil, I., Othman, N.S., Khreishah, A., Guizani, M.: Unmanned aerial vehicles (uavs): A survey on civil applications and key research challenges. *IEEE access* **7**, 48572–48634 (2019)
- [74] Zhao, Y., Zhang, J., Zhang, C.: Deep-learning based autonomous-exploration for uav navigation. *Knowledge-Based Systems* **297**, 111925 (2024)
- [75] Boiteau, S., Vanegas, F., Gonzalez, F.: Framework for autonomous uav navigation and target detection in global-navigation-satellite-system-denied and visually degraded environments. *Remote Sensing* **16**(3), 471 (2024)
- [76] Elmokadem, T., Savkin, A.V.: Towards fully autonomous uavs: A survey. *Sensors* **21**(18), 6223 (2021)
- [77] Soliman, A., Al-Ali, A., Mohamed, A., Gedawy, H., Izham, D., Bahri, M., Erbad, A., Guizani, M.: Ai-based uav navigation framework with digital twin technology for mobile target visitation. *Engineering Applications of Artificial Intelligence* **123**, 106318 (2023)
- [78] Traspadini, A., Giordani, M., Giambene, G., De Cola, T., Zorzi, M.: On the energy consumption of uav edge computing in non-terrestrial networks. In: 2023 57th Asilomar Conference on Signals, Systems, and Computers, pp. 1684–1690 (2023). IEEE
- [79] Zhang, Y., Zhao, R., Mishra, D., Ng, D.W.K.: A comprehensive review of energy-efficient techniques for uav-assisted industrial wireless networks. *Energies* **17**(18), 4737 (2024)
- [80] Liu, J., Zhang, X., Zhou, H., Lei, X., Li, H., Wang, X.: Lyapunov-based deep deterministic policy gradient for energy-efficient task offloading in uav-assisted

mec. Drones **9**(9), 653 (2025)

- [81] Zhang, Q., Furqan, M.D., Nutzhat, T., Machida, F., Andrade, E.: Dependability of uav-based networks and computing systems: a survey. arXiv preprint arXiv:2506.16786 (2025)
- [82] Wang, N., Christen, M., Hunt, M., Biller-Andorno, N.: Supporting value sensitivity in the humanitarian use of drones through an ethics assessment framework. *International Review of the Red Cross* **104**(919), 1397–1428 (2022)
- [83] Won, J., Kim, D.-Y., Park, Y.-I., Lee, J.-W.: A survey on uav placement and trajectory optimization in communication networks: From the perspective of air-to-ground channel models. *ICT Express* **9**(3), 385–397 (2023)
- [84] Bithas, P.S., Michailidis, E.T., Nomikos, N., Vouyioukas, D., Kanatas, A.G.: A survey on machine-learning techniques for uav-based communications. *Sensors* **19**(23), 5170 (2019)
- [85] Chen, H., Lin, Y., Fu, M., Yao, L., Sheng, M.: A survey on reinforcement learning methods for uav systems. *ACM Computing Surveys* **58**(4), 1–37 (2025)
- [86] Li, S., Hu, X., Du, Y.: Deep reinforcement learning for computation offloading and resource allocation in unmanned-aerial-vehicle assisted edge computing. *Sensors* **21**(19), 6499 (2021)
- [87] Suleiman, A., Zhang, Z., Carlone, L., Karaman, S., Sze, V.: Navion: A 2-mw fully integrated real-time visual-inertial odometry accelerator for autonomous navigation of nano drones. *IEEE Journal of Solid-State Circuits* **54**(4), 1106–1119 (2019)
- [88] Ahmad, S., Ahmad, R., Al-Shamayleh, A.S., Nimma, D., Zaman, M., Ivković, N., Cengiz, K., Akhunzada, A., Haider, E.: Flight into the future: a holistic review of ai-trends, vision, and challenges in drones technology. *Artificial Intelligence Review* (2025)
- [89] Kang, M., Park, M.: Power estimation and energy efficiency of ai accelerators on embedded systems. *Energies* **18**(14), 3840 (2025)
- [90] Hazare, G., Sultan, M.T.H., Łukaszewicz, A., Nowakowski, M., Shahar, F.S.: Charting smarter skies—a review of computational strategies for energy-saving flights in electric uavs. *Energies* **18**(24), 6521 (2025)
- [91] Ai, Y., Liu, C., Li, M.: Energy-efficient uplink communication in uav-enabled mec networks with pinching antennas. *Drones* **9**(11), 796 (2025)
- [92] Manjarrez, L.H., Ramos-Fernández, J.C., Espinoza, E.S., Lozano, R.: Estimation of energy consumption and flight time margin for a uav mission based on fuzzy

systems. Technologies **11**(1), 12 (2023)

- [93] Anoune, K., El Kafazi, I., El Maliki, A., Bossoufi, B., Nasiri, B., Zekraoui, H., Almalki, M.M., Alghamdi, T.A., Alenezi, M.: Performance enhancement of drone lib state of charge using extended kalman filter algorithm. Cleaner Engineering and Technology **25**, 100917 (2025)
- [94] Ferrag, M.A., Lakas, A., Debbah, M.: Uavbench: An open benchmark dataset for autonomous and agentic ai uav systems via llm-generated flight scenarios. arXiv preprint arXiv:2511.11252 (2025)