REVIEW ARTICLE

AI Integration in Unmanned Aerial Vehicles: Key Challenges, Enabling Technologies, and Practical Solutions

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Abstract

Over the last decade, Unmanned Aerial Vehicle (UAV) technology has rapidly developed by integrating AI tools and methodologies. UAVs are used across many fields, including wireless communication, logistics, agriculture, construction, security, and exploration. UAV systems are inherently complex and present numerous challenges. This study conducted a systematic literature review to identify the main challenges and the solutions researchers have proposed. A total of 141 research papers were collected and analyzed, with no restriction on publication year. The review identified 10 main challenges affecting AI in UAVs. These include problems with autonomous navigation, real-time decision-making, network and sensor limits, limited computational power, poor communication and coordination, high energy consumption, hardware and payload restrictions, security and privacy issues, path planning and collision avoidance, and limited battery life. In addition, the review identified over 100 solutions/practices, including lightweight AI models, improved communication systems, energy-efficient methods, and enhanced security measures. This review is useful for both researchers and practitioners. It clearly organizes the challenges and solutions, identifies gaps for future research, and offers practical ideas for building better UAV systems. Solving these challenges will make UAVs more reliable and effective in many sectors, leading to improvements in safety, productivity, and economic growth.

Keywords: artificial intelligence, unmanned aerial vehicles, AI integration in UAVs, systematic literature review, challenges of AI in UAVs.

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1 Introduction

Unmanned aerial vehicles (UAVs), commonly known as drones, are aircraft systems that operate without a human pilot onboard and are generally operated remotely or autonomously [1, 9]. Over the last decade, dramatic advances in Artificial Intelligence (AI) and robotics have increased interest in UAVs among academic and industrial communities. UAVs are particularly applicable to tasks that require access to dangerous, inaccessible, or remote locations [43]. The integration of AI has increased UAV functionality to a large extent, thus they are now capable of performing complicated autonomous operations. The UAVs, though initially designed as military equipment, have been utilized in a wide range of activities and in non-military business work. These include logistics and cargo transport, environmental surveillance (e.g. air pollution, surface land temperature, flood control, forest fires), road and terrain surveillance, pedestrian traffic surveillance, disaster response, agriculture, construction, surveillance, exploration, mobile wireless communication, and search and rescue operations [2, 3]. AI-powered UAVs can also be of great economic benefit, as they can automate these activities, reducing costs, and improving efficiency in different sectors.

Regardless of these wide-ranging uses and advantages, there are a number of challenges related to AI-integrated UAV systems that have not been tackled. Among the problems, high rate of energy consumption, data sensing and collection, the limitation of real-time processing, high requirements of autonomous operation are the challenges that prevent the common and effective implementation of autonomous AI-driven UAVs. Currently, advances in computational hardware and software have made AI an integral part of almost every discipline of engineering [4]. AI has been especially useful in the pursuit of complex and data-intensive problems that could not be tackled using traditional approaches or required significant human intervention. Unresolved challenges can adversely affect economic viability due to higher operational cost, reduced scalability, and the need to spend a lot on infrastructure and maintenance costs. Consequently, they constitute an impediment to the affordability of the implementation of AI-based UAV solutions in sectors. Modern UAVs Powered by AI can perform fully autonomous or partially autonomous functions. These systems can sense the surroundings and make smart decisions in real time using the information provided by the onboard sensors and devices that are attached to them [5].

There are multiple uses of AI techniques in navigation, motion planning and control using GPS, computer vision, and machine learning algorithms. In addition, AI empowers UAVs to handle complex tasks such as voice recognition, scene understanding, object detection, and image classification, especially through deep learning approaches.

Several recent studies have explored deep learning (DL) techniques in UAV applications, revealing gaps in current capabilities and opportunities for improvement. For instance, assessments of machine learning-based UAV communication systems have typically focused on limited use cases, often lacking depth in algorithmic evaluation. Likewise, vision-based AI systems for UAV navigation have been applied to search and rescue and surveillance scenarios [6], while others have examined AI-driven UAVs in mission planning for rescue operations [7], early detection of agricultural diseases [8], and intelligent traffic management, monitoring, and control [10]. Although many studies have looked at using AI in UAV systems, most of them focus on only one area or a single type of algorithm. Because of this, there is still a limited understanding of how AI can be fully integrated into UAVs. As AI becomes more advanced, new challenges appear, such as hardware limits, delays in real-time decision-making, the complexity of AI models, and the need for reliable performance in critical situations. These challenges can affect how well UAVs perform and how easily they can be scaled for wider use. Therefore, it is important to study these problems carefully and look for general solutions that can help improve AI applications in UAVs.

The generalized framework of this study is illustrated in Figure 1. In this research, a systematic literature review (SLR) approach was adopted to investigate the integration of Artificial Intelligence (AI) into Unmanned Aerial Vehicle (UAV) applications. The analysis identifies the key challenges and the corresponding solutions reported in existing studies, providing a structured framework for addressing AI integration challenges in UAV systems. The purpose of the present study is to explore these challenges and answer specific research questions that provide a complete view of current progress in this field.

RQ1: What are the challenges faced in integrating artificial intelligence into UAV applications?

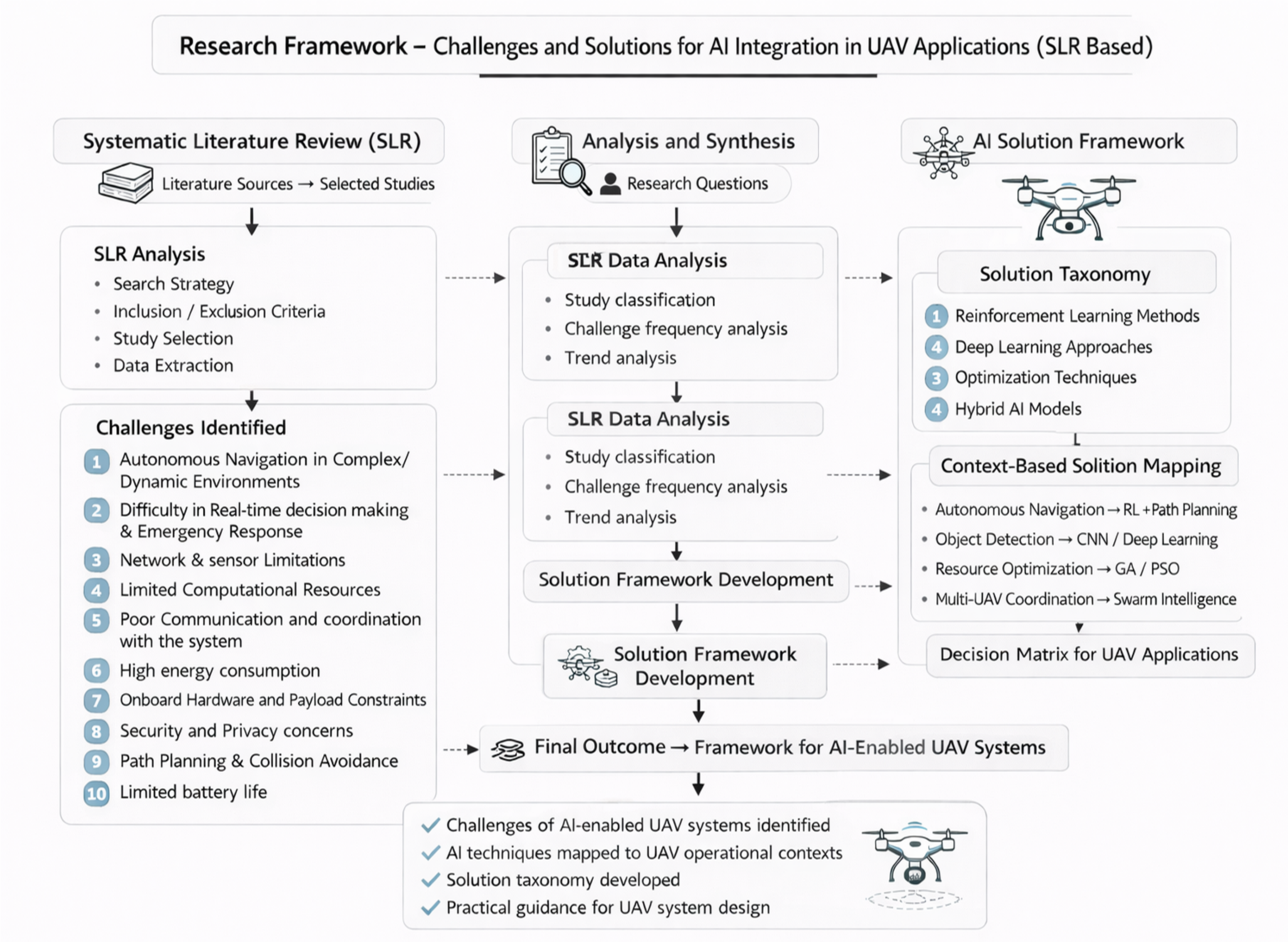

Figure 1. A generalized overview of challenges and solutions for integrating AI into UAV applications.

RQ2: What solutions have been proposed to address these challenges in AI-integrated UAV systems?

The remainder of this paper is structured as follows: In Section 2, the context and background of the study are presented. Section 3 provides the research methodology used. In Section 4, the findings of the SLR are described. Section 5 illustrates the results analysis and discussion. Section 6 demonstrates the practices for the identified challenges of integrating AI into UAV applications. Section 7 represents limitations and threats to validity, and lastly, the conclusion is represented in Section 8.

2 Related Work

Unmanned Aerial Vehicles (UAVs), widely recognized as drones, have become crucial in the advancement of numerous civil and commercial domains due to their efficiency in operating in hazardous, inaccessible, or remote environments [11]. Their integration into diverse fields such as precision agriculture, infrastructure assessment, logistics, surveillance, and emergency response has substantially enhanced operational capabilities by enabling rapid deployment, real-time data acquisition, and minimizing human exposure to risk [12]. The increasing utilization of UAVs as autonomous monitoring and task-performing platforms underscores their potential to reshape conventional. Artificial Intelligence (AI) technologies have developed at a very fast pace in parallel, allowing UAVs to complete tasks independently without human intervention. AI-driven UAVs can now perform complex operations such as object detection, path planning, obstacle avoidance, and real-time decision-making. ML, DL, and Reinforcement Learning (RL) are some of the techniques that have greatly increased the capabilities of UAVs by enabling the enhancement of perception, navigation, and control systems [3].

Numerous survey studies have been conducted to investigate the application of AI in UAV systems. For example, Caballero-Martin et al. [3] presented a cutting-edge analysis of AI algorithms used in drone control, emphasizing their effects on decision-making effectiveness, autonomy, and logistics. Similarly, Albeaino et al. [13] carried out a detailed analysis of UAV applications in the AEC (Architecture, Engineering, and Construction) industry, located technological components of the UAV-based monitoring and inspection system, such as platform types, control modes, and UAV-mounted sensors. Sornek et al. [44] presented an overview of the status of UAVs in remote sensing applications. Ham et al. [14] discussed UAV applications in the visual inspection of civil infrastructure systems. Duque et al. [18] presented UAV implementations for post-construction infrastructure inspections with a specific focus on the departments of Transportation (Dots). In addition, few studies address the practical constraints that arise during real-time UAV operations. Recently, Betalo et al. [45] explored the role of Generative AI (GAI) in enabling swarm intelligence among UAVs, demonstrating promise for decentralized decision-making, collaborative mapping, and autonomous coordination. These developments open new directions, but they also raise critical concerns regarding reliability, scalability, and ethical implications in safety-critical systems. Khan et al. [19] presented a comprehensive study on emerging UAV technologies for disaster detection, mitigation, response, and preparation. Their work emphasizes the role of UAVs in improving situational awareness and supporting emergency operations through real-time data collection and rapid deployment capabilities. Although their focus lies primarily in the domain of disaster management. The reviewed studies show that combining AI with UAVs offers great potential but also presents serious challenges. Many researchers have used AI methods such as machine learning, deep learning, and reinforcement learning to improve UAV performance, but most of this work focuses on narrow technical or domain-specific areas. As UAVs become more intelligent, concerns such as limited computing power, real-time response, data privacy, and reliability are becoming more important. These challenges need to be clearly identified and connected to possible solutions. However, based on current knowledge, there is no complete SLR that examines these challenges and the ways to solve them. For this reason, this study conduct an SLR to bring together existing research, find key challenges, and highlight useful solutions for better AI-based UAV systems, supporting both future research and practical development.

3 Methodology

We formulated this research study in a structured manner to comprehensively address both the challenges and solutions related to the integration of AI into UAV applications. To achieve this, we conducted an SLR that systematically investigates the reported challenges associated with AI integration into UAV systems, as well as existing solutions, methods, and best practices documented in the literature to overcome these challenges. The SLR is a rigorous protocol-driven method widely used in the field of software engineering and technological research domains. Unlike Ordinary Literature Reviews (OLRs), SLRs follow predefined guidelines, ensuring transparency and reproducibility in the data collection, analysis, and synthesis process. According to established practices [15–17, 22], the SLR process typically falls into three main stages:

- Planning the Review – Defining the research questions, search strategy, and inclusion/exclusion criteria.
- Conducting the Review – Identifying and selecting relevant literature from academic databases and source of Gray literature, followed by data extraction.
- Reporting the Review – Synthesizing findings, presenting identified factors and practices, and discussing implications for research and application in AI-based UAV systems.

As Kitchenham et al. [46] noted, "a systematic literature review is a way of finding, assessing, and understanding all existing studies related to a specific research question, subject zone, or phenomenon of interest." The SLR approach not only enhances the credibility and depth of our findings but also helps bridge the gap between academic research and practical application. The remainder of the paper presents the design, execution and outcomes of the SLR with clear documentation of each step taken. This systematic approach provides a high level of consistency in findings, facilitates knowledge sharing, and ensures that both theoretical and applied perspectives are addressed comprehensively [47]. Figure 2 illustrates the steps followed to perform the SLR. It outlines the systematic process adopted to ensure a comprehensive and rigorous review.

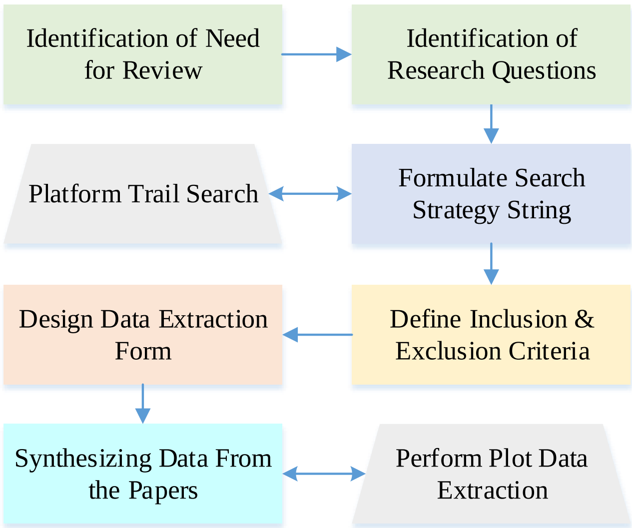

Figure 2. Steps to conduct SLR.

3.1 Planning the review

The main steps involved in conducting a review are as follows.

3.1.1 *Identification of the Need for the Review*

In order to determine whether any previous Systematic Literature Reviews (SLR) had specifically addressed the integration of Artificial Intelligence (AI) in Unmanned Aerial Vehicle (UAV) applications, we manually reviewed a large number of papers and conference proceedings before starting this study. However, according to our research, no previous SLR in the official academic literature thoroughly examined this subject. There is no systematic synthesis of current knowledge and practices in AI-enabled UAV systems instead, most existing research focuses on discrete technical features or specific challenges. This finding highlighted the need to methodically identify and compile the main obstacles and workable solutions in AI-UAV integration, revealing a significant gap in the literature.

3.1.2 *Research questions*

RQ1: What are the challenges faced in integrating artificial intelligence (AI) into UAV applications?
RQ2: What practices or solutions have been proposed to address these challenges in AI-enabled UAV applications?

3.1.3 *Construction of Search Terms*

To construct the search term, the RQs are first analyzed in four different perspectives of population, intervention, outcome of relevance, and experimental design to identify search terms. It is performed by comparing the keywords within the RQs. The search terms are first based on keywords in the RQs, and the search strings are created using a structure known as PICO, [20, 21] The mechanism adopted for the construction and identification of the search terms is as follows: First, by determining the population, intervention, and result that are relevant, different search terms are extracted from the study questions.

Population: UAVs
Intervention: Challenges/solutions
Comparison: For the current study, no comparisons are made. Outcome of Relevance: We aim to explore the challenges and their solutions and to advance practices in UAV systems to increase the efficiency, productivity, and quality of AI integration in UAV applications.

Outcome: Integration of Artificial Intelligence (AI) in UAV applications **Experimental Design:** The experimental design contains SLR, empirical studies or evaluative studies, case studies, white papers, expert opinions, blog posts, and observations.

RQ1: [What are the key challenges] INTERVENTION [Integration of Artificial Intelligence (AI)] OUTCOME OF RELEVANCE In [Unmanned Aerial Vehicles (UAVs) applications] POPULATION RQ2: [What are the Solution/practices] INTERVENTION [Integration of Artificial Intelligence (AI) applications]OUTCOME In [Unmanned Aerial Vehicles (UAVs)] POPULATION

3.2 Search Strategy and Identification of Search Terms

The search strategy was designed to find challenges and solutions/practices for research questions in accordance with the SLR set guidelines [41]. The main factors that we identified using the PICO framework are population (UAV), intervention (challenges and solutions), and result (AI integration in UAV applications). The main search terms were based on these factors and the necessary synonyms and alternative spellings were determined during a preliminary review of related sources. Keywords were checked with the literature that was already available to be relevant and comprehensive. The search strings were constructed using Boolean operators: Synonyms were combined using OR, and the key ideas were connected using AND. Long search strings were shortened or broken down when needed to fit the database constraints. This was done in a systematic way that would ensure effective and accurate retrieval of the relevant studies in the review.

3.2.1 Search string For SLR:

A structured search string was created and used in the selected digital libraries according to the research objectives and identified keywords.

("Challenge" OR "factor" OR "issue" OR Solution" OR "Practices" OR "Methods) AND ("Artificial intelligence" OR "AI") AND ("UAV" OR "Unmanned Aircraft System" OR "Unmanned Aerial System" OR "Remotely Piloted Aircraft" OR "Drone")

3.2.2 Selection of Data Sources

This research was limited to peer-reviewed scholarly materials (White Literature) to ensure high quality and reliability. The selection process was organized in a systematic manner to include pertinent, high-quality studies on the use of Artificial Intelligence (AI) in UAV systems, and the work included in the review process will be significant to the purposes of the review.

3.2.3 Sources searched

The sources for this review were selected digital libraries and indexing databases, identified through automated search and snowballing procedures following [52]. To collect the needed literature, we selected the following accepted academic resources and digital libraries having access to relevant materials: IEEE Xplore [1], ACM Digital Library [2], ScienceDirect [3], SpringerLink [4], and Wiley Online Library [5]. These databases were selected because they cover a wide range of literature in computer science, AI and software engineering. They offer good search options, as well as access to full text journal articles, conference proceedings, and other peer-reviewed materials in full text. It ensures that the chosen studies are of excellent academic quality and that they are closely dedicated to the objectives of the SLR. Based on these academic sources, the study examines the literature to provide information on the challenges and solutions of AI applications in UAV systems.

3.2.4 Selection of Publications

The publication selection criteria will focus on selecting papers that are closely related to the research questions. Specifically, we have considered studies related to the deployment of Artificial Intelligence (AI) in the integration of Unmanned Aerial Vehicles (UAVs) and points such as AI-based navigation, object recognition, flight optimization, and autonomous decision-making in UAVs. Articles will be excluded when they talk about UAV without AI, or AI without UAV usage. We reviewed titles, abstracts, full text, and content and conducted quality assessments to select suitable articles. This selection process aims to gather relevant and high-quality literature by applying specific inclusion and exclusion criteria. To support our SLR, we established the following criteria. Figure 3 illustrates the publication selection process.

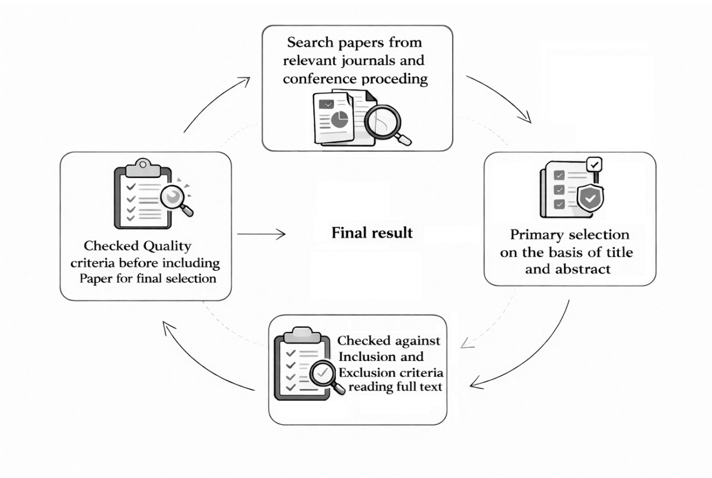

Figure 3. Publication selection criteria.

3.2.5 Primary Selection

Primary study selection began with a review of titles, keywords, and abstracts to eliminate irrelevant publications and select articles that were related to the research questions. Selected studies were then evaluated in full text against the inclusion and exclusion criteria. A secondary reviewer would review any cases of uncertainty to maintain consistency and minimize selection bias. This process ensured a rigorous and consistent selection of relevant literature.

3.2.6 Inclusion criteria

The inclusion criteria were used to identify which scholarly literature (e.g., journal articles, conference papers, and technical reports) retrieved through the search terms would be selected for data extraction. Only publications written in English were included. The criteria are listed below:

- IC1: Studies that identify challenges, barriers, or limitations related to the integration of Artificial Intelligence (AI) into Unmanned Aerial Vehicle (UAV) systems.
- IC2: Research that proposes, evaluates,

[1] http://ieeexplore.ieee.org
[2] http://dl.acm.org
[3] https://www.sciencedirect.com
[4] http://www.springerlink.com
[5] https://onlinelibrary.wiley.com

or discusses solutions, frameworks, or methodologies to address integration issues between AI and UAV technologies.

- IC3: Studies that focus on AI-based enhancements in UAV functionalities, such as navigation, object detection, path planning, or autonomous decision-making.
- IC4: Articles written in English and available in full text from peer-reviewed journals, conference proceedings, or recognized technical reports.
- IC5: Both empirical and theoretical studies that provide insights into real-world implementations, simulations, or conceptual models related to AI-UAV integration.

3.2.7 Exclusion Criteria

This section describes the exclusion criteria that will be applied to determine which parts of the literature collected by the search term will be ignored or excluded. The following is an outline of the standards.

- EC1 Research papers that don't specifically answer the questions about how artificial intelligence might be incorporated into UAV applications.
- EC2 Papers that do not address the integration of Artificial Intelligence (AI) into Unmanned Aerial Vehicle (UAV) applications.
- EC3 Articles that focus solely on hardware aspects of UAVs without discussing AI integration.
- EC4 Publications where the full text is not available.
- EC5 Non-scholarly sources such as blogs, magazine articles, white papers, and other forms of gray literature.
- EC6 Duplicate studies or versions of the same study published in multiple venues.

3.2.8 Publication quality assessment

A detailed quality assessment was conducted for every study included in the final stage, ensuring that only high-quality, methodologically robust publications informed the review. We applied a three-point Likert scale ("Yes," "Partially," and "No") and developed specific quality assessment criteria to evaluate each element of the selected publications. For each criterion, we assigned a score of 2 for "Yes," 1 for "Partially," and 0 for "No" to ensure the reliability of the evaluation. Publications with an average quality score greater than 0.5 were considered to meet the minimum threshold and included in the SLR. Table 1 lists the quality assessment questions used in the evaluation process.

Table 1. Quality assessment criteria.

S.No	Criteria for Quality Assessment	Likert Scale
1	Does the paper identify challenges in integrating Artificial Intelligence into UAV applications?	Yes / No
2	Does the paper present solutions, practices, methodologies, or best practices for effectively applying AI in UAV applications to address those challenges?	Yes / No

3.2.9 Data Extraction

Data extraction was all included studies to systematically obtain the information required to address the research questions. This procedure will involve evaluating the entire text and subsequently sorting the information that appears pertinent. Table 2 lists the specific details that must be found in every study:

Table 2. Data to be extracted from selected studies.

S.No	Data to Be Extracted
1	Paper ID
2	Date of Review
3	Title of the Study
4	Author(s)
5	Source/Database (e.g., IEEE Xplore, ACM Digital Library, ScienceDirect, Wiley Online Library, SpringerLink)
6	Research Methodology (e.g., interview, case study, experimental study, survey)
7	Publication Year
8	Identified challenges in integrating Artificial Intelligence into UAV applications (technical, ethical, environmental, or regulatory)
9	Proposed solutions, practices, or frameworks for effectively implementing AI in UAV systems

3.2.10 Procedure for Study Selection

The tollgate strategy was used to select and filter research articles accessed using the stated search

Table 3. Result of finally selected articles for SLR.

Database	No. of Publications	Initial Selection	Final Selection
ACM Digital Library	516	93	31
IEEE Xplore	564	68	36
ScienceDirect	811	106	33
SpringerLink	231	23	20
Wiley Online Library	786	28	10
Snowballing	–	–	10
Total	**2908**	**318**	**141**

strings in digital libraries and other pertinent sources of gray literature. Other SLRs researchers have also applied a similar tollgate method [40, 42] to refine and filter retrieved studies in a systematic manner. This action plan involves five consecutive steps that are described in the following section.

- To locate relevant research papers, we performed search strings in digital libraries and databases.
- To determine whether an article would be included or excluded, we evaluated the abstract and heading.
- To make more inclusion/exclusion decisions, we looked at the introduction and conclusions.
- We reviewed the entire article to evaluate whether it should be included in our investigation.

3.2.11 Preliminary Results

Following the execution of the search strings and the application of the inclusion and exclusion criteria, a Systematic review of the literature (SLR) was conducted to address two research questions: challenges in integrating AI into UAV applications and the related solutions and best practices. The initial search across major digital libraries, academic databases, and relevant web sources identified 2,908 articles, including both published and unpublished studies to reduce publication bias. These records were gathered to answer the research questions presented in Section 1. The selection process was carried out in two stages. First,the selection of titles and abstract screening reduced the dataset to 318 studies that met the preliminary criteria. Second, a full text review resulted in 131 eligible studies. Additionally, 10 relevant studies were identified through the snowballing technique. This resulted in a final set of 141 high-quality articles included in the SLR. Table 3 presents the final number of selected studies.

3.2.12 Data Synthesis

The data for SLR has been organized for SLR into two summary tables based on the research questions. These tables include columns for serial numbers, identified challenges, frequencies, and percentages, offering a comprehensive overview of all the main challenges associated with integrating AI into UAV applications, along with how frequently each challenge appears and its relative significance. In addition, a separate table has been developed to record detailed information about each identified challenge. This table includes columns for the name of the challenge group, the reference serial number, challenge subcategories, and the references on paper.

3.3 Snowballing

Snowballing refers to a supplementary literature search methodology that is applied to reveal more pertinent literature by searching the reference lists (backward snowballing) and citations (forward snowballing) of preselected articles. In this research, snowballing has been used so that the coverage of literature could be more exhaustive and comprehensive to include closely related studies that otherwise might not have been found by the main search of the database. This methodology assisted in increasing the completeness, reliability, and rigor of the literature selection process by eliminating the possibility of excluding important and highly relevant publications.

4 Results

This section presents the results obtained from the SLR. It describes the key findings of the study and provides an analysis of the challenges and solutions identified while addressing the research questions (RQ1 and RQ2). Through the SLR process, a total of 10 major challenges related to the integration of artificial intelligence into UAV applications were identified, as summarized in Table 4, while the

Table 4. Identified challenges in AI-enabled UAV applications.

S. No	Challenges	References of Papers	Frequency (n=141)	Percentage (%)
1	Autonomous navigation in complex/dynamic environments	1, 3, 4, 5, 8, 11, 12, 15, 18, 19, 20, 23, 24, 25, 33, 35, 37, 43, 46, 51, 52, 54, 56, 57, 58, 60, 61, 62, 64, 65, 67, 70, 71, 72, 73, 74, 75, 77, 78, 80, 81, 82, 84, 85, 86, 87, 88, 93, 95, 96, 97, 98, 99, 101, 102, 103, 109, 110, 111, 112, 113, 114, 117, 119, 120, 121, 122, 123, 124, 125, 127, 128, 129, 130, 131, 133, 134, 135, 136, 140, 141	81	57
2	Difficulty in real-time decision making and emergency response	1, 2, 3, 4, 7, 8, 11, 12, 18, 23, 26, 42, 46, 47, 49, 50, 51, 53, 54, 55, 57, 58, 59, 62, 63, 67, 77, 83, 91, 93, 96, 97, 98, 99, 100, 103, 106, 107, 108, 109, 111, 113, 119, 120, 121, 126, 127, 128, 133, 135, 136, 139	52	36
3	Network & sensor limitations	3, 7, 8, 9, 12, 23, 25, 30, 31, 35, 41, 44, 46, 47, 49, 53, 54, 56, 59, 60, 61, 62, 64, 65, 68, 74, 77, 79, 81, 82, 93, 94, 100, 101, 104, 107, 111, 115, 117, 118, 119, 127, 128, 131, 132, 133, 135	47	33
4	Limited computational resources	1, 7, 8, 16, 19, 23, 32, 42, 48, 52, 55, 59, 60, 61, 62, 67, 76, 79, 83, 84, 88, 93, 96, 98, 100, 104, 107, 113, 114, 117, 118, 122, 123, 124, 129, 133, 134, 135, 140, 141	40	28
5	Poor communication and coordination with the system	5, 12, 34, 50, 51, 53, 54, 60, 64, 68, 69, 72, 75, 77, 78, 82, 86, 87, 89, 93, 95, 97, 102, 103, 104, 106, 107, 111, 116, 117, 118, 125, 128, 133, 134, 137, 139	37	26
6	High energy consumption	7, 8, 51, 53, 56, 75, 82, 84, 91, 95, 97, 98, 100, 101, 103, 105, 107, 108, 110, 112, 113, 114, 115, 116, 118, 124, 132, 133, 134, 135, 137, 138, 139, 140	34	24
7	Onboard hardware and payload constraints	3, 7, 8, 11, 12, 16, 23, 28, 36, 47, 49, 51, 55, 68, 69, 82, 84, 93, 101, 108, 110, 114, 121, 124, 128, 134, 135, 139, 140, 141	30	21
8	Security and privacy concerns	Privacy: 2, 6, 7, 15, 44, 49, 52, 53, 54, 65, 77, 84, 90, 91, 92, 96, 104, 107, 111, 113, 116, 133, 134, 137, 140	25	18
9	Path planning and collision avoidance	12, 23, 33, 51, 52, 56, 57, 64, 67, 74, 77, 92, 102, 103, 104, 105, 107, 111, 112, 113, 114, 120, 126, 129, 133	25	18
10	Limited battery life	28, 29, 37, 50, 55, 58, 69, 76, 77, 93, 104, 105, 111, 116, 132, 133, 140	17	12

frequency distribution of these challenges is illustrated in Figure 4. Among the identified challenges, three are categorized as critical challenges (Cs). The criterion used to determine whether a challenge is considered critical is based on its frequency of occurrence in the selected publications. A challenge is considered critical if it appears in more than 30% of the reviewed studies. Similar criteria have also been used in previous studies [13, 23, 24]. However, industry practitioners who work with UAV systems may adopt different thresholds depending on the application context. The following subsections first present the detailed results related to the identified challenges in order to address RQ1 and RQ2. After presenting these results, additional analyses were conducted to further examine the characteristics and distribution of the selected studies. The details of these analyses are provided in section 5.

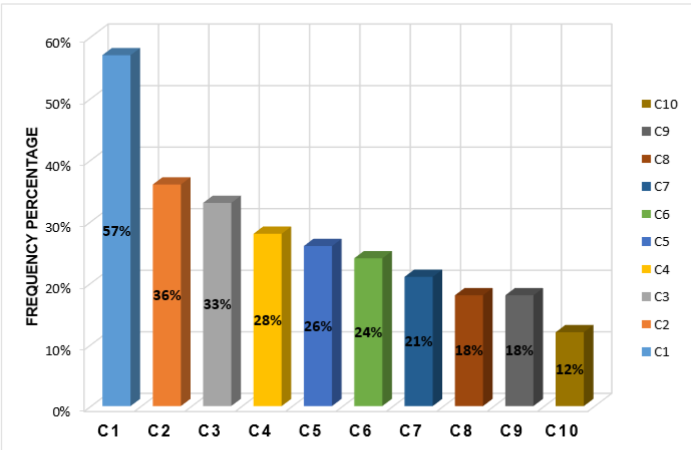

Figure 4. Frequency percentage of the identified challenges in AI-integrated UAV applications.

4.1 Challenges integrating AI into UAV applications

C1. Autonomous Navigation in Complex/Dynamic Environments: Autonomous Navigation in Complex / Dynamic Environments is the most common challenge, appearing in 81 of 141 articles, with a frequency of 57%. Therefore, Autonomous navigation in complex and dynamic environments is a critical challenge in integrating AI into UAV applications. These environments are unpredictable, with moving objects, dynamic obstacles, and changing terrain [25, 26]. UAVs must perceive their surroundings in real-time using sensors such as LiDAR, cameras, and radar [48]. Path planning is challenging due to the constant changes that require fast adaptive replanning existing algorithms often fail to guarantee collision-free paths in dynamic settings.The Handling uncertainty and partial observability remains an open problem [38]. Real-time decision-making under resource constraints adds additional complexity, ensuring robust, safe, and efficient navigation in real world dynamic environments remains an unsolved challenge [27].

C2. Difficulty in Real-time Decision Making & Emergency Response: Difficulty in real-time decision making is the second most common challenge identified in the reviewed literature, occurring in 52 out of 141 articles, with a frequency of 36%. It is also one of the most prominent and critical challenges in UAV and AI-based systems, particularly in high-stakes or unpredictable scenarios. These systems must process sensor data, assess risk, and make decisions in milliseconds—all under limited computational resources and uncertain conditions [28]. Delays or failures in this process can lead to mission failure or safety hazards, especially during emergency response operations [49]. To improve the safety, reliability, and responsiveness of UAV and AI-based systems working in a dynamic and high-risk environment, it is crucial to address the challenge of real-time decision making and response to emergencies [29].

C3. Network & sensor Limitations: The third challenge in the integration of Artificial Intelligence into UAV applications mentioned most frequently is network and sensor limitations, which are cited in 47 of the 141 reviewed studies with frequencies of (33%). Fast and quality data transfer is essential to support AI systems in consuming and making timely decisions, but UAVs often work in regions of low, unreliable, or random network access. This restricts the exchange of real-time data interchange between the UAV and ground control, or cloud-based AI models [30]. Similarly, sensor limitations, such as poor resolution, limited range, or improper configuration, may lead to incorrect or inadequate data acquisition [50]. A large amount of data is needed to make AI algorithms effective, so these limitations can substantially affect the effectiveness and reliability of AI-driven UAV systems [31, 53].

C4. Limited computational resources: Limited computational resources are the fourth critical challenge in integrating Artificial Intelligence into UAV systems. Most UAVs are constrained by size, weight, and power limitations, which restrict their ability to carry powerful onboard processors required for AI tasks such as real-time object detection, path planning, and autonomous navigation. As a result, running complex AI models onboard becomes difficult, often leading to delays, reduced accuracy, or dependence on remote servers via unstable communication links[9]. Furthermore, the need for energy-efficient computing further limits the type and scale of AI algorithms that can be deployed on UAVs. These constraints can severely impact mission-critical applications such as disaster response or military surveillance, where real-time intelligence is crucial. Recent studies highlight the need for lightweight AI models and edge computing strategies tailored for UAV environments to overcome these challenges [32].

C5. Poor communication and coordination with systems: Poor communication and coordination with systems is the fifth most common challenge, with a frequency of 26%. Ineffective communication between UAVs and supporting systems—such as ground control stations, cloud servers, or other UAVs,can lead to data loss, delays, or conflicting operations. This is particularly critical in swarm or multi-agent missions requiring synchronized actions. Such poor coordination can significantly reduce system efficiency and mission success rates [9, 34].

C6. High energy consumption: High energy consumption is a significant challenge in the integration of AI into UAV applications, with a frequency 24% of the reviewed studies. Running AI algorithms, especially for tasks like real-time object detection or autonomous navigation, requires substantial computational power, which quickly drains UAV batteries. Limited battery life reduces flight time, limits operational range, and affects overall mission efficiency. This challenge is more critical in long-duration or multi-UAV missions where energy management is vital [4, 35].

C7. Onboard hardware and payload constraints: Onboard hardware and payload constraints have been identified in 21% of the reviewed studies as a significant challenge in integrating AI into UAV systems. UAVs also have a small payload and should be aerodynamically stable and be able to fly efficiently, making it difficult to install several advanced systems. [11]. These limitations directly impact the integration of AI modules that require space for processing units and support systems. Hardware constraints such as limited processing power, memory, and heat dissipation capabilities make it difficult to execute complex AI algorithms in real time and increase energy consumption [32]. Payload constraints further limit the weight and size of additional components, restricting the use of high-end sensors or computing hardware. Exceeding payload capacity can lead to reduced flight time, poor maneuverability, and increased energy usage, ultimately affecting mission success and system reliability [33].

C8. Security and privacy concerns: Security and privacy concerns were identified in 18% of the reviewed studies as a major challenge in AI-integrated UAV systems. UAVs are vulnerable to cyber attacks, such as GPS spoofing, jamming, and unauthorized access, which can compromise flight control and mission data. Additionally, AI models handling sensitive information (e.g., surveillance footage) raise serious privacy issues. Unauthorized data collection or breaches can lead to legal and ethical problems. Ensuring secure communication and privacy-sensitive AI processing is crucial for reliable UAV deployment [36, 37].

C9. Path planning and collision avoidance: Path planning and collision avoidance emerged as a key challenge in 18% of the reviewed studies, highlighting the complexity of autonomous UAV navigation. In fast-changing environments, UAVs must make split-second decisions to avoid obstacles, terrain, and other flying objects. Even minor sensing delays or inaccurate mapping can result in near misses or dangerous collisions. The high-risk nature of aerial operations makes this challenge both technically demanding and mission-critical [51].

C10. Limited battery life: Limited battery life was identified in 12% of the reviewed studies as a key challenge in AI-integrated UAV systems. The computational demands of AI algorithms significantly increase power consumption, placing additional strain on already limited energy resources. This leads to reduced flight duration and restricted mission capabilities, especially in long-range or real-time processing tasks. Limited battery life remains a persistent challenge to fully understanding the potential of AI in UAV operations [39].

5 Analysis and Discussion

This section presents a comprehensive analysis and discussion of the selected studies on the integration of AI into UAV systems. The analysis is conducted from multiple perspectives, including the study methodology, continent, publication venue, and year of publication. This multi-dimensional examination helps identify key research trends and provides deeper insights into the most frequently reported challenges in the existing literature.

Table 5. Overview of research methodologies employed in the selected studies.

S. No	Challenges	Experiment (N=89)		Other Methods (N=52)	
		F	%	F	%
1	Autonomous Navigation in Complex/Dynamic Environments	51	57	38	73
2	Difficulty in Real-time decision-making & Emergency Response	34	38	18	35
3	Network & Sensor Limitations	27	30	16	31
4	Limited Computational Resources	23	25	16	31
5	Poor Communication and Coordination with other systems	17	19	20	38
6	High Energy Consumption	15	17	19	36
7	Onboard Hardware and Payload Constraints	18	20	9	17
8	Security and Privacy Concerns	8	9	17	33
9	Path Planning Collision Avoidance	14	16	10	19
10	Limited Battery Life	9	10	8	15

5.1 Analysis Based on Study Methodology

We grouped the final sample of selected articles into six categories based on the research methodologies used in the studies, as shown in Table 5. The identified methodological categories include experiments, ordinary literature reviews (OLR), systematic literature reviews (SLR), case studies, surveys, and other or mixed methods. The "other/mixed methods" refers to studies that apply more than one research methodology in a single article. The distribution of these methodologies is illustrated in Figure 5. The results show that experimental studies represent the most widely used research methodology, accounting for 89 of the 141 selected articles. Ordinary literature reviews constitute the second largest group with 16 papers. Similarly, survey-based studies and mixed-method approaches each appear in 12 papers, while case studies represent the smallest category with 4 papers. To better understand the relationship between research methodologies and the reported challenges, we analyze how frequently each challenge appears within the different methodological categories. Table 5 presents a comparative overview of the identified challenges in the six methodology groups: experiments, ordinary literature reviews (OLR), SLR, surveys, case studies, and mixed methods.

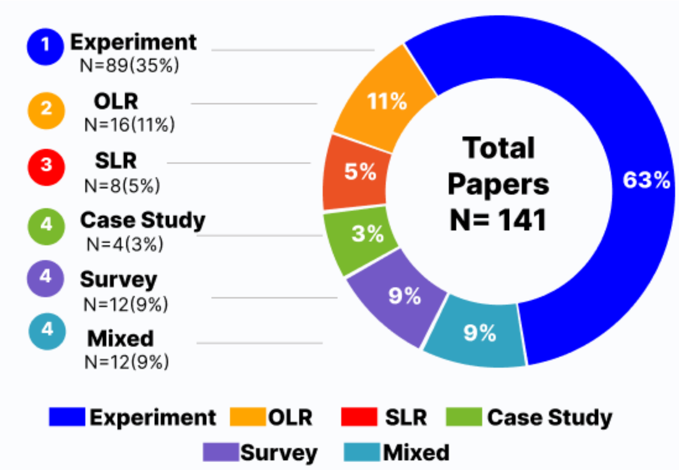

Figure 5. Overview of research methodologies employed in the selected studies.

The analysis shows that all ten identified challenges are reported in studies employing experimental, OLR, SLR, survey, and mixed methodologies, while seven of the ten challenges are reported in case study based research. Across the reviewed literature, several challenges frequently appear within specific methodological categories. For example, "Autonomous Navigation in Complex/Dynamic Environments" is the most reported challenge in experimental studies (57%). In reviews of the ordinary literature, both "Autonomous Navigation in Complex/Dynamic Environments" (56%) and "Network and Sensor Limitations" (50%) are frequently highlighted. In systematic literature review studies, "Network and Sensor Limitations" appears to be one of the commonly reported challenges (50%). Case study-based research reports several challenges

Table 6. Distribution of selected studies across continents.

S. No	Challenges	Asia (N=50)		Europe + USA + Others (N=91)	
		F	%	F	%
1	Autonomous Navigation in Complex/Dynamic Environments	23	46	58	64
2	Difficulty in Real-time decision making & Emergency Response	19	38	33	36
3	Network & Sensor Limitations	20	40	27	30
4	Limited Computational Resources	15	30	25	27
5	Poor Communication and Coordination with System	9	18	28	31
6	High Energy Consumption	13	26	21	23
7	Onboard Hardware and Payload Constraints	10	20	20	22
8	Security and Privacy Concerns	15	30	10	11
9	Path Planning Collision Avoidance	9	18	16	18
10	Limited Battery Life	6	12	11	14

with comparable frequency, including "Autonomous Navigation in Complex/Dynamic Environments," "Difficulty in Real-Time Decision Making and Emergency Response," "Poor Communication and Coordination with the System" and "Onboard Hardware and Payload Constraints," each appearing in approximately 50% of the studies. In survey-based studies, the most frequently reported challenges include "Autonomous Navigation in Complex/Dynamic Environments" (50%), "Poor Communication and Coordination with the System" (58%), and "High Energy Consumption" (50%). Similarly, in mixed-method studies, "Autonomous Navigation in Complex/Dynamic Environments" appears most prominently, reported in 83% of studies within this category. In general, the results indicate that certain challenges, particularly autonomous navigation, communication limitations, and energy consumption, are consistently reported in multiple research methodologies. This suggests that these challenges represent fundamental technical barriers in the integration of artificial intelligence within UAV systems.

5.2 Analysis of the Identified challenges Based on Continent

Table 6 presents a comparative overview of the identified challenges in relation to the continents where the studies were conducted or published. Some studies included in the SLR report research conducted across multiple regions, however, the majority of the literature focuses on three main continents: Europe, Asia, and America, while the remaining studies are grouped under other regions, as illustrated in Figure 6. The objective of this regional comparison is to explore whether the emphasis on certain challenges differs between geographical contexts.

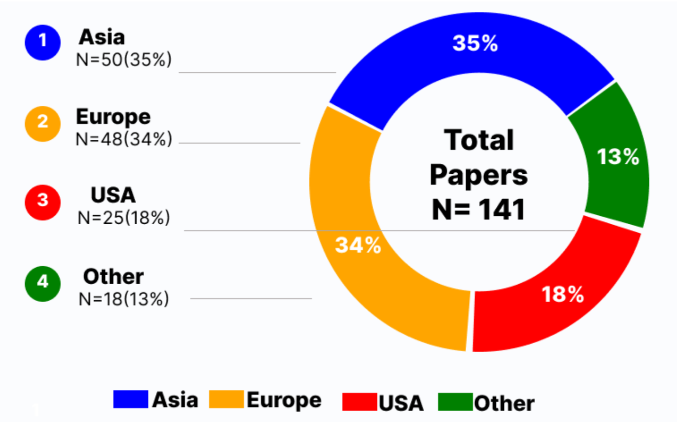

Figure 6. Distribution of selected studies across continents.

Although the identified challenges appear across multiple continents, a closer examination reveals that their prominence is influenced by region-specific contextual factors. In Europe and North America, regulatory restrictions and the issue of airspace integration are frequently emphasized due to the presence of strict aviation regulations and highly structured UAV governance frameworks. Research originating from these regions often highlights challenges related to certification, safety assurance,

Table 7. Distribution of the selected studies by publication source.

S. No	Challenges	Conference (N=35)		Journal (N=106)	
		F	%	F	%
1	Autonomous Navigation in Complex/Dynamic Environments	18	51	63	59
2	Difficulty in Real-time decision making & Emergency Response	12	34	40	37
3	Network & Sensor Limitations	12	34	35	33
4	Limited Computational Resources	9	26	31	29
5	Poor Communication and Coordination with System	4	11	33	31
6	High Energy Consumption	1	3	33	31
7	Onboard Hardware and Payload Constraints	7	20	23	22
8	Security and Privacy Concerns	6	17	19	18
9	Path Planning Collision Avoidance	3	9	22	21
10	Limited Battery Life	2	6	15	14

and compliance with evolving aviation authority guidelines, which significantly shape the design and deployment of UAV systems.

In contrast, studies conducted in Asia tend to focus more strongly on scalability, real-time processing, and energy efficiency. This emphasis is largely driven by dense urban environments, large-scale UAV deployments, and the rapid growth of AI-enabled drone applications in areas such as smart cities, logistics, and surveillance. In addition, infrastructure-related challenges, including reliable communication networks and edge-computing capabilities, are frequently discussed due to the need for efficient UAV operation in highly dynamic and densely populated environments.

Research in Africa and South America is comparatively limited, but often highlights challenges associated with infrastructure limitations, limited computational resources, and environmental sustainability. Studies in these regions commonly address practical deployment issues, such as operating UAV systems in remote locations, limited network connectivity, and harsh environmental conditions that can affect system reliability and performance. In general, while core technical challenges—such as energy constraints, real-time decision-making, and system reliability—are globally recognized, their relative emphasis varies between regions. These variations reflect differences in regulatory frameworks, infrastructure maturity, deployment environments, and application priorities. Consequently, while similarities highlight shared technological limitations in UAV systems, the differences illustrate how regional contexts shape the way these challenges are addressed in different parts of the world.

5.3 Analysis of the Identified challenges Based on Publication Venue

Table 7 presents an analysis of the selected studies based on their publication venues. The final set of publications identified through the SLR includes articles published in journals, workshops, conferences, and symposiums. For the purpose of analysis, these publication venues were grouped into two primary categories: journals and conferences. As shown in Table 7, the majority of the selected studies were published in journals, accounting for approximately 75% of the final sample. In contrast, approximately 25% of the studies were published in conferences and related venues, as illustrated in Figure 7.

Based on this distribution, the identified challenges were examined in the two publication categories. The analysis indicates that ten major challenges are discussed in both journal and conference publications. Among these challenges, "Autonomous Navigation in Complex/Dynamic Environments" appears most frequently in both venues. Specifically, this challenge is reported in 51% of the journal articles and 59% of the conference article included in the final dataset. This finding highlights the widespread recognition

Table 8. Distribution of studies by publication year.

S. No	Challenges	2008-2016 (N=6)		2017-2025 (N=135)	
		F	%	F	%
1	Autonomous Navigation in Complex/Dynamic Environments	5	83	76	56
2	Difficulty in Real-time Decision Making & Emergency Response	5	83	47	35
3	Network & Sensor Limitations	4	67	43	31
4	Limited Computational Resources	0	0	40	30
5	Poor Communication and Coordination with System	5	83	32	23
6	High Energy Consumption	1	16	33	24
7	Onboard Hardware and Payload Constraints	3	50	27	20
8	Security and Privacy Concerns	1	16	25	18
9	Path Planning Collision Avoidance	4	67	21	16
10	Limited Battery Life	1	16	16	12

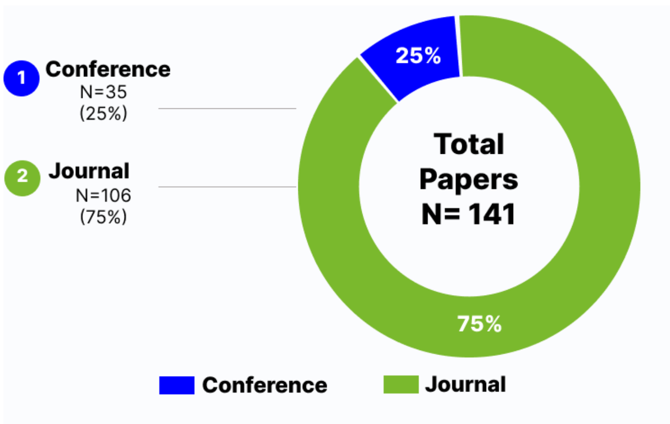

Figure 7. Distribution of selected studies across publication sources.

of autonomous navigation in dynamic environments as a critical research challenge in UAV systems across different publication platforms. Overall, the distribution of challenges between journals and conferences suggests that both publication venues emphasize similar research issues, although journals tend to contain a larger proportion of the studies included in this review.

5.4 Analysis of the Identified challenges Based on the Year Published

Table 8 presents an analysis of the selected studies based on the publication year, while Figure 8 compares the challenges identified over two time periods. No specific time restrictions were applied during the systematic literature review search process. However, research contributions related to UAV applications began to emerge more prominently around 2008. For analytical purposes, the years of publication were divided into two periods: Period 1 (2008–2016) and Period 2 (2017–2025).

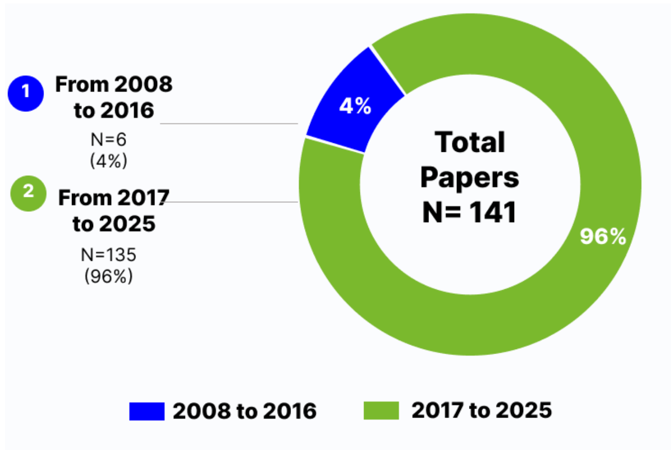

Figure 8. Number of studies published per year.

The results indicate that the research output during the first period (2008–2016) was relatively limited. Only one article was published in 2008 and 2009, no publications were identified in 2010 and 2013, while two articles were reported in 2014 and 2016. In general, the number of studies during this early period remained low. In contrast, a clear increase in research activity can be observed from 2017 onward. One study was published in 2017, followed by six articles in 2018 and eight articles in 2019. The research output continued to grow significantly, reaching a peak of 46 publications in 2024, while 2025 had already reported 12 publications at the time of this study, as illustrated in Figure 9.

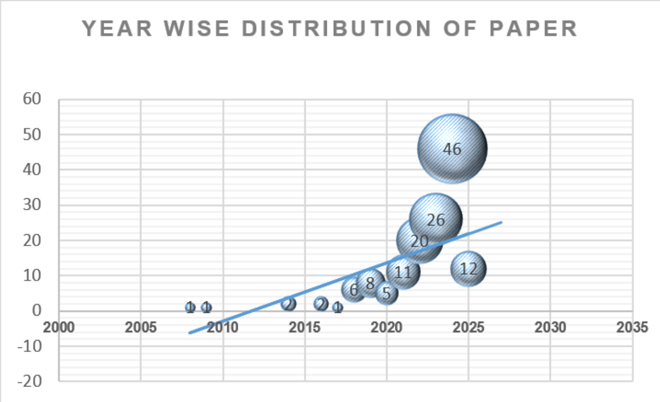

Figure 9. Distribution of selected studies by publication year.

The comparison between the two periods highlights the rapid growth of interest in the integration of artificial intelligence with UAV systems. Most publications are concentrated in the second period (2017–2025), indicating a growing focus of research on AI-enabled UAV technologies. This increasing number of studies also reflects the ongoing efforts of researchers to address the technical and operational challenges associated with the deployment of AI in UAV systems. Despite the growing body of research, several challenges remain unresolved, suggesting that further investigation and innovative solutions are still required to support the effective and reliable deployment of AI-powered UAV applications.

6 Technical Synthesis of Challenges

The review of the studies helps reveal the most important technical challenges of AI-enabled UAV systems, the new research direction, and how they all relate to each other. The implications of future research in the given synthesis are also outlined, which can guide on the areas that need to be studied further and combined solutions.

6.1 Dominant Technical Challenges

The analysis of the studies reviewed indicates that several challenges appear consistently in different domains of UAV application. Among them, autonomous navigation in complex and dynamic environments, real-time decision-making, and network and sensor limitations emerge as the most frequently discussed challenges. These issues reflect the fundamental technical difficulties involved in enabling UAVs to operate autonomously in real-world environments. Autonomous navigation appears to be the most dominant challenge in the literature. This prominence can be attributed to the inherent complexity of UAV operation in dynamic environments where obstacles, weather conditions, and moving objects constantly change. Effective navigation requires the integration of perception, localization, and adaptive path planning, which remain active areas of research in AI-enabled robotics. Similarly, real-time decision-making is widely reported because UAV systems must process large volumes of sensor data and respond within strict time constraints. In mission-critical applications such as disaster response or surveillance, delays in decision-making can significantly affect operational reliability. Network and sensor limitations also appear frequently due to the reliance of UAV systems on continuous data acquisition and communication. Limited sensor accuracy, unreliable wireless connectivity, and bandwidth constraints often reduce the effectiveness of AI-based perception and coordination mechanisms.

6.2 Emerging Research Trends

The distribution of publications in recent years indicates a rapid growth in research interest in AI-enabled UAV systems, particularly after 2017. This increase is likely driven by advances in deep learning, edge computing, and autonomous robotics, which have expanded the capabilities of UAV platforms. As UAV applications continue to expand in sectors such as logistics, agriculture, environmental monitoring, and disaster management, researchers are increasingly focusing on overcoming the practical challenges associated with AI deployment in aerial systems. Another noticeable trend is the increasing emphasis on resource-efficient AI models. Many studies propose lightweight architectures and edge-based computing approaches to address the computational and energy constraints of UAV platforms.

6.3 Interrelationship Between Challenges

The identified challenges are not independent rather, they are closely interconnected. For example, limited computational resources directly affect the ability of UAVs to perform real-time decision-making and complex navigation tasks. Similarly, energy consumption constraints influence both onboard processing capabilities and communication reliability. These inter-dependencies suggest that addressing individual challenges in isolation may not be sufficient.

Instead, integrated solutions that combine efficient AI models, improved communication architectures, and energy aware system design are necessary to support reliable AI-enabled UAV operations.

6.4 Implications for Future Research

The findings of this analysis highlight several directions for future research. First, there is a need for lightweight and energy-efficient AI models capable of performing real-time inference on resource-constrained UAV platforms. Second, improved communication and coordination mechanisms are required to support multi-UAV and swarm-based operations. Finally, enhanced security and privacy mechanisms must be developed to ensure safe deployment of UAV systems in sensitive environments. In general, the analysis indicates that although significant progress has been made in integrating AI into UAV systems, several technical and operational challenges remain open research problems that require multidisciplinary solutions.

7 solutions/practices for the identified challenges integrating AI into UAVs applications

The integration of Artificial Intelligence (AI) techniques in Unmanned Aerial Vehicle (UAV) systems has significantly Improved capabilities such as autonomous navigation, environmental perception, mission planning, and decision-making. However, the large number of AI-based solutions proposed in the literature presents challenges to practitioners who are trying to select the most appropriate solution for specific UAV operational scenarios. To address this issue, this section organizes the identified solutions into a structured framework consisting of a solution taxonomy, context-based solution mapping, a decision matrix, and a critical evaluation of the proposed techniques. This framework provides practical guidance for researchers and practitioners by linking AI solutions to specific operational contexts and highlighting their advantages and limitations. Although Tables 10, 11, 12, 13, 14, 15, 16, 17, 18 and 19 provide a comprehensive list of proposed solutions/practices to address identified challenges, their synthesis reveals several important trends and priorities. Several high-impact, deployment-ready practices are widely adopted in UAV systems. These include reinforcement learning and deep Q-learning for autonomous navigation and real-time decision-making, AI-driven path planning algorithms, lightweight AI models such as TinyML, MobileNet, and YOLO for resource-constrained platforms, and edge computing architectures that enable onboard processing with reduced latency.

In addition, multimodal sensor fusion techniques are frequently used to overcome sensor and communication constraints, while swarm intelligence and adaptive communication protocols improve coordination among multiple UAVs. Energy-aware algorithms and hybrid energy solutions are also commonly applied to extend the operational endurance of UAV. From a security perspective, techniques such as end-to-end encryption, secure communication protocols, blockchain-based data acquisition, and intrusion detection systems are widely employed to Improve system reliability and data privacy. In contrast, several emerging research directions remain at an experimental stage, including the integration of reinforcement learning with genetic algorithms and neural networks for adaptive control, decentralized multi-agent reinforcement learning, improved collision avoidance strategies using PPO and transformer networks, and experimental energy optimization strategies combining deep reinforcement learning, federated learning, and wireless energy harvesting.

In addition, techniques such as adaptive path-finding algorithms, automated alert and notification systems, and sensor fusion based decision architectures have demonstrated strong potential in time-sensitive applications. Lightweight onboard execution frameworks and energy-aware routing algorithms are particularly suitable for resource-constrained UAV deployments. However, certain advanced deep learning models used for image recognition and environmental perception provide high accuracy but often require significant computational power and energy resources. In general, these findings indicate that no single solution is universally applicable to all operational challenges of UAV. Instead, the selection of appropriate strategies depends on mission requirements, environmental conditions, computational constraints, and safety requirements. Therefore, a structured framework is required to guide practitioners in selecting suitable AI techniques for specific operational contexts of UAV. The following subsections present a solution taxonomy, context-based solution mapping, and a decision matrix that link AI techniques to practical UAV mission scenarios.

Table 9. AI solutions/practices for Different UAV operational scenarios.

Operational Context	Recommended AI Solutions/Practices	Key Advantages	Limitations
Urban low-altitude navigation	Reinforcement learning (PPO, DQN), transformer-based path planning, and multi-sensor fusion (camera, LiDAR, IMU)	Adaptive obstacle avoidance and improved navigation accuracy in dense environments	High training complexity and computational requirements
Rural or wide-area surveillance	Optimization algorithms (GA, PSO), Probabilistic Roadmap (PRM) planning, and lightweight CNN models with edge processing	Efficient long-distance route planning and large-area coverage	Limited adaptability to highly dynamic environments
Search and rescue operations	YOLO-based human detection models, real-time sensor fusion, and reinforcement learning decision systems	Fast and accurate victim detection with improved situational awareness	High computational requirements for real-time processing
Multi-UAV swarm missions	Multi-agent reinforcement learning, federated learning, and adaptive communication protocols	Cooperative decision-making and improved coordination among UAV fleets	Complex training procedures and communication overhead
Large-scale mission planning	Transformer networks and AI-based global path optimization techniques	Ability to process large datasets and plan complex missions	High computational cost and training requirements
Resource-constrained UAV platforms	TinyML architectures, MobileNet or lightweight YOLO models, and edge computing frameworks	Reduced computational load and energy consumption	Possible reduction in prediction accuracy
Disaster response and time-critical missions	Real-time sensor fusion systems, automated alert frameworks, and reinforcement learning decision support	Rapid decision-making and enhanced situational awareness	Dependence on sensor quality and communication stability
Security-sensitive UAV operations	Blockchain-based communication, encryption protocols, and AI-based intrusion detection systems	Enhanced data integrity and secure communication	Additional system overhead and implementation complexity
High-precision navigation	Advanced multi-sensor fusion techniques	Improved environmental perception and navigation accuracy	Increased hardware cost and system complexity

7.1 Solution Taxonomy

To systematically organize the large number of solutions identified in the literature, a solution taxonomy was developed to classify AI techniques used in UAV systems according to their methodological characteristics. The taxonomy groups solutions into four main categories: reinforcement learning-based methods, deep learning approaches, optimization-based techniques, and hybrid AI models. Reinforcement learning (RL) techniques are widely used in UAV applications that require adaptive decision-making in dynamic and uncertain environments. Algorithms such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) enable UAVs to learn optimal navigation strategies through continuous interaction with the surrounding environment. These techniques are particularly effective in autonomous navigation tasks where environmental conditions frequently change. Deep learning approaches are commonly applied in UAV perception and data analysis tasks. Models such as Convolutional Neural Networks (CNNs) and Transformer-based architectures allow UAV systems to process large volumes of sensory data, perform object detection, and interpret environmental information. These techniques are widely used in applications such as target recognition, obstacle detection, and environmental monitoring. Optimization-based techniques address mainly deterministic planning problems such as path optimization, task allocation, and resource scheduling. Algorithms such as Genetic

Table 10. Autonomous navigation in complex/dynamic environments.

S. No	C1 Practices for Autonomous Navigation in Complex/Dynamic Environments	Frequency	Paper-ID
CP1.1	Use of Reinforcement Learning (RL) to train drones in simulated dynamic wind environments.	14	3, 7, 9, 10, 12, 19, 24, 36, 46, 50, 61, 100, 101, 117
CP1.2	Integration of reinforcement learning, genetic algorithms, and neural networks for adaptive control.	13	3, 10, 12, 19, 24, 57, 88, 100, 101, 117, 125, 133, 134
CP1.3	Integrate AI-based path planning algorithms (e.g., A* algorithm, deep Q-learning) to allow drones to autonomously navigate complex environments.	12	3, 28, 31, 30, 35, 67, 99, 102, 103, 108, 126, 139
CP1.4	Proposed a novel, explainable AI-based navigation approach for autonomous UAV navigation in unknown environments.	10	4, 5, 13, 19, 81, 86, 91, 94, 110, 133
CP1.5	Used the YOLO algorithm for fast and efficient human detection, even in challenging environments.	9	1, 29, 40, 42, 48, 49, 104, 136, 139
CP1.6	Develop AI-driven fault detection systems and backup control mechanisms to enhance safety and reliability during autonomous operations.	7	3, 7, 79, 102, 117, 126, 128
CP1.7	Integrate contingency structures and fallback procedures into AI behavior models for autonomous decision-making.	4	8, 23, 76, 78
CP1.8	Use Multi-sensor fusion (LiDAR + IMU + cameras).	7	3, 65, 81, 103, 110, 114, 135
CP1.9	Use of Proximal Policy Optimization (PPO) algorithm for adaptive learning and robust navigation.	5	51, 61, 74, 84, 121
CP1.10	Leverage edge AI to distribute the training and inference processes by splitting the large, complex environment into multiple smaller environments.	3	135, 137, 111

Table 11. Difficulty in real-time decision making and emergency response.

S. No	C2 Practices for Real-time Decision Making and Emergency Response	Frequency	Paper-ID
CP2.1	Implement reinforcement learning and deep learning algorithms for faster, real-time decision-making.	13	3, 7, 9, 10, 12, 19, 24, 36, 46, 50, 61, 100, 106
CP2.2	AI (e.g., reinforcement learning) enables adaptive, real-time decision-making in dynamic environments.	7	3, 7, 12, 46, 88, 106, 133
CP2.3	Use Deep Q-Networks (DQNs) trained via federated learning for local and global decision-making.	3	7, 41, 50
CP2.4	Implement Multi-Agent Reinforcement Learning (MARL), where each MD makes decisions based on local observations.	3	7, 84, 107
CP2.5	Integrate machine learning and edge AI for automated, rapid data analysis use UAV swarms for large area coverage.	3	7, 110, 135
CP2.6	Integrate AI-based analytics for real-time data processing and communication.	2	3, 54
CP2.7	Development of high-autonomy systems with embedded AI to enable dynamic, real-time decision-making.	2	12, 13
CP2.8	Design of onboard decision support systems (DSS) leveraging knowledge-based systems and rule-based systems.	1	12
CP2.9	Utilized frame-dropping to ensure faster decision-making without compromising detection quality.	1	1

Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are commonly used to determine efficient flight paths and mission strategies in relatively stable environments. Hybrid AI approaches combine multiple techniques to take advantage of different methods. For example, reinforcement learning can be integrated with optimization algorithms to improve path planning performance, while deep learning models can be combined with reinforcement learning frameworks to enhance perception-driven decision making. These hybrid approaches are particularly suitable for

Table 12. Network and sensor limitations.

S. No	C3 Practices for Network and Sensor Limitations	Frequency	Paper-ID
CP3.1	Designed a multi-modal sensor fusion system (MUTES) combining microphones, cameras, and LIDAR.	7	3, 127, 65, 81, 103, 110, 135
CP3.2	Use AI techniques like sensor fusion to combine data from multiple sensors (e.g., cameras, LIDAR) for more accurate environment understanding.	6	3, 8, 23, 12, 46, 127
CP3.3	Use a combination of advanced sensor technologies, including Multitask Cascading CNN, ScatterNet Hybrid Deep Learning Network, multiscale infrared optical flow, and event-based vision and SLAM, to overcome these limitations.	5	9, 11, 47, 55, 110, 122
CP3.4	Deep reinforcement learning and federated learning for decentralized routing and topology decisions.	4	7, 94, 107, 134
CP3.5	Federated Learning (FL) with secure aggregation DRL-based intrusion detection systems secure routing protocols integrated with AI.	3	104, 134, 94
CP3.6	ML optimizes data routes AI handles GPS failures via dynamic rerouting blockchain secures drone-C2 links.	3	44, 53, 116
CP3.7	Use of network topology-aware heuristics (e.g., Highest Node Degree method for replica placement).	2	58, 76
CP3.8	Delegation of optimization tasks to UAVs simplified fuzzy c-means clustering approach for UAV selection.	1	118
CP3.9	Offload planning computation using edge/cloud systems or compact, onboard AI models.	1	128
C3.10	Develop AI/ML methods to analyze the sensor data and detect various crowd behaviors, including crowd density, speed, pose, and movement, as well as identify violent individuals.	1	13

complex UAV missions that involve both perception and adaptive control.

7.2 Context-Based Solution Mapping

Although the taxonomy provides a structural classification of AI techniques, practitioners often need guidance in selecting appropriate solutions for specific operational contexts of UAV. Therefore, the identified solutions were mapped to common UAV mission scenarios. Autonomous navigation in low-altitude urban environments typically involves dynamic obstacles, unpredictable wind conditions, and dense infrastructure. In such scenarios, reinforcement learning techniques such as PPO and deep Q-learning are particularly effective because they allow UAVs to continuously adapt to dynamic environmental changes. For rural surveillance and long-distance monitoring missions, optimization algorithms such as genetic algorithms and particle swarm optimization are more suitable because they efficiently compute optimal routes across large geographic areas while minimizing energy consumption. In search and rescue operations, deep learning-based perception models such as YOLO-based object detection algorithms are widely used for rapid human detection and situational awareness in complex environments. Similarly, multi-UAVs coordination tasks benefit from multi-agent reinforcement learning techniques that allow multiple UAVs to learn cooperative strategies and coordinate their actions effectively. For high-precision navigation tasks, multi-sensor fusion techniques that combine LiDAR, cameras, and inertial measurement units significantly improve environmental perception and navigation accuracy. This context-based mapping enables practitioners to select the most appropriate AI solutions/practices based on mission characteristics, environmental complexity, and operational constraints.

7.3 Decision Matrix for Practitioners

To further support practical decision-making, a decision matrix was developed to link UAV operational scenarios with the most appropriate AI solution, as shown in Table 9. This matrix provides a simplified guide for practitioners in selecting AI approaches for different mission requirements.

The decision matrix serves as a practical reference that enables practitioners to select appropriate AI techniques according to mission

Table 13. Limited computational resources.

S. No	C4 Practices for Limited Computational Resources	Frequency	Paper-ID
CP4.1	Leveraged the lightweight YOLO algorithm and frame-dropping to optimize performance with limited hardware.	4	1, 40, 42, 49
CP4.2	Design and optimize lightweight AI models (e.g., SSDLite-MobileNetV3) that run efficiently on embedded hardware.	3	8, 83, 93
CP4.3	Lightweight AI models (e.g., TinyML) for edge processing.	3	122, 113, 135
CP4.4	Deploy lightweight AI models optimized for edge computing. Use efficient architectures like TinyML for UAVs.	2	8, 134
CP4.5	Utilize parallel processing and A3C-based learning for scalable, efficient AI training and deployment.	2	100, 107
CP4.6	AI with hierarchical or distributed architectures offline training + online inference strategy (e.g., DNN, CNN, HJB).	1	107
CP4.7	Use deep learning compression, hardware accelerators (e.g., TrueNorth), and distributed AI frameworks.	1	117
CP4.8	Use of event-by-event and frame-like event processing approaches to balance responsiveness with computational efficiency.	1	124
CP4.9	Efficient encoding and selective simulation-based validation reduce the real-time processing burden.	1	129
CP4.10	Use cloud-based simulation and AI Wings platform.	1	133
CP4.11	Multi-access Edge Computing (MEC) – Offload AI computations to edge servers or the cloud.	1	140
CP4.12	Optimize neural network architecture to reduce computational and energy costs.	1	139

Table 14. Poor communication and coordination with system.

S. No	C5 Practices for Poor Communication and Coordination	Frequency	Paper-ID
CP5.1	Swarm system designed to be resilient to communication failures.	6	72, 64, 107, 116, 133, 134
CP5.2	Knowledge Distillation, edge AI, and FL to reduce communication overhead.	2	7, 137
CP5.3	Apply M/G/1 multi-class queuing model for accurate end-to-end delay analysis and optimization.	1	50
CP5.4	Implement gossip-based communication systems and explore global vs. local training/execution communication modes.	1	51
CP5.5	Use of Lamport clocks, OFDM, and QAM to model communication bandwidth and ordering.	1	64
CP5.6	Combine speech with gestures, gaze, facial expressions, head nods.	1	68
CP5.7	Link budget enhancement via optimized drone positioning for improved RSS and throughput.	1	82
CP5.8	Provide thorough education and transparent communication about UAV capabilities and limitations.	1	78
CP5.9	Design UAVs to elicit trust through familiar elements and clear communication of intentions.	1	87
CP5.10	Implement adaptive communication protocols. Utilize decentralized AI models to reduce data transmission needs.	1	134

requirements, environmental complexity, and available computational resources.

Table 15. High energy consumption.

S. No	C6 Practices for High Energy Consumption	Frequency	Paper-ID
CP6.1	Empirical power modeling of UAVs for different flight phases (hovering, vertical, horizontal) to optimize energy use.	6	75, 76, 91, 98, 103, 104
CP6.2	Develop a comprehensive energy consumption model and apply adaptive behavior based on battery thresholds.	3	50, 105, 114
CP6.3	Design energy-aware AI algorithms. Optimize inference processes to balance power and performance.	3	76, 110, 134
CP6.4	Developing hybrid power systems combining different power sources (fuel cell, battery, solar cell, super capacitor) and using AI for intelligent energy management.	3	37, 75, 118
CP6.5	Energy-aware algorithms (EEMSIoT and UAV-GreenMS) that minimize total energy consumption.	3	76, 91, 103
CP6.6	Use lightweight deep reinforcement learning algorithms (e.g., PPO, SAC, A2C).	3	19, 84, 97
CP6.7	Energy-aware heuristics optimize flight paths and processing tasks.	2	112, 122
CP6.8	UAVs equipped with wireless power transfer modules to recharge sensors online energy queue optimization.	2	104, 118
CP6.9	Quantize models to int8 and use dedicated accelerators (e.g., GAP9 NE16) to reduce memory and energy use.	1	93
CP6.10	Optimize neural network architecture to reduce computational and energy costs.	1	139
CP6.11	AI-based energy optimization and route planning algorithms.	1	133
CP6.12	Use edge computing and lightweight AI models.	1	135

Table 16. Onboard, Hardware, and Payload Constraints.

S. No	C7 Practices for Onboard, Hardware, and Payload Constraints	Frequency	Paper-ID
CP7.1	Install lightweight AI models optimized for edge computing. Use efficient architectures like TinyML for UAVs.	8	46, 86, 93, 94, 113, 134, 135, 139
CP7.2	Implement lightweight models (e.g., Tiny YOLOv3, MobileNet-SSD) or cloud offloading strategies.	7	1, 47, 49, 83, 88, 135, 139
CP7.3	Lightweight sensors (MEMS LiDAR, Jetson boards).	6	3, 103, 110, 114, 131, 135
CP7.4	Adoption of miniaturized, lightweight event cameras and onboard low-power computers.	5	3, 81, 124, 127, 141
CP7.5	Leverage online resources and cloud services like RoboEarth.	4	49, 68, 128, 140
CP7.6	Developed a lightweight live correction algorithm decoupled from heavy sensory data (e.g., vision).	4	1, 8, 84, 101
CP7.7	Offloading heavy computation to companion computers use of onboard optimized hardware (e.g., Pixhawk + PX4).	3	79, 84, 141
CP7.8	Use SLAM, sensor fusion (e.g., GPS + camera + IMU), and distributed perception sharing across UAV-UGV teams.	3	82, 117, 132
CP7.9	Optimize AI models for efficient processing on hardware with limited resources, like edge computing and hardware accelerators (e.g., GPUs).	2	3, 120
C7.10	Offload planning computation using edge/cloud systems or compact, onboard AI models.	1	129
CP7.11	System design includes combined payload for seamless AI, imaging, and communication functions.	1	82

7.4 Comparative Analysis of Key solutions/practices

A comparative analysis was conducted to evaluate the strengths and limitations of the main AI solutions/practices used in UAV systems. Reinforcement learning techniques offer strong adaptability and are particularly suitable for

Table 17. Security and Privacy concerns.

S. No	C8 Practices for Security and Privacy	Frequency	Paper-ID
CP8.1	Strengthen security protocols, restrict access, and apply encrypted communication.	8	2, 5, 7, 77, 87, 92, 103, 104
CP8.2	Adopt encryption and secure communication to protect data integrity.	5	2, 53, 92, 96, 140
CP8.3	Apply end-to-end encryption, federated learning, and decentralized data space.	5	53, 104, 134, 94, 96
CP8.4	Ensure confidentiality and integrity using secure communication protocols.	4	2, 77, 91, 133
CP8.5	Use encrypted AI, blockchain identity verification, and secure channels.	4	44, 53, 91, 94
CP8.6	Develop secure onboard processing and UAV cyber security mechanisms.	4	49, 90, 92, 111
CP8.7	Implement blockchain-based data acquisition with privacy protection.	4	44, 96, 113, 116
CP8.8	Secure routing and path planning to avoid malicious UAVs using DRL.	3	100, 107, 104
CP8.9	Apply Q-learning intrusion detection and secure communication protocols.	3	133, 134, 136
CP8.10	Use private channels and identity management for secure UAV communication.	2	53, 96
CP8.11	Deploy ML-based intrusion detection and fault detection models.	1	113
CP8.12	Evaluate security and robustness using simulation testing.	1	84
CP8.13	Apply privacy-preserving AI and randomization techniques.	1	134

dynamic environments where UAVs must respond to changing conditions in real time. However, these methods typically require extensive training time and substantial computational resources. Deep learning models provide powerful pattern recognition perception and capabilities. They are highly effective for tasks such as object detection, environmental monitoring, and image-based target recognition. Nevertheless, these models often require large training datasets and high-performance hardware, which can limit their deployment on lightweight UAV platforms. Optimization algorithms provide efficient solutions for deterministic planning tasks such as route optimization and mission scheduling. These techniques are computationally efficient and relatively easy to implement, but may struggle to adapt to rapidly changing environmental conditions. Hybrid AI approaches attempt to overcome these limitations by combining multiple techniques. Although such approaches can provide improved adaptability and performance, they often increase system complexity and implementation difficulty. In general, comparative analysis indicates that no single AI technique is universally optimal for all UAV applications, and the selection of appropriate methods should depend on mission requirements, environmental conditions, and system constraints.

7.5 Limitations of Proposed Solutions

Although AI-based Solutions/Practices significantly enhance UAV capabilities, several limitations and trade-offs must be considered when deploying these solutions/practices in real-world environments. Reinforcement learning approaches typically require large training datasets and extensive computational resources. In addition, models trained in simulated environments may not always generalize effectively to real-world conditions, potentially affecting the reliability of the system. Deep learning-based perception models, such as YOLO-based object detection algorithms, provide high accuracy but often require powerful onboard hardware. This requirement increases energy consumption and can limit their deployment on lightweight UAV platforms. Similarly, lightweight AI models designed for resource constrained UAV systems reduce computational

Table 18. Path Planning Collision Avoidance.

S. No	C9 Practices for Path Planning Collision Avoidance	Frequency	Paper-ID
CP9.1	Use PPO-based TSP solver for optimal way point path planning and coverage.	4	51, 61, 74, 121
CP9.2	Use of a dual-model AI architecture combining ResNet8 (DL) and Res-DQN (DRL) for path prediction and avoidance.	3	7, 23, 107
CP9.3	Use of PRM (Probabilistic Road map Method) over A* for better time performance in high-agent scenarios.	3	52, 57, 103
CP9.4	Application of Transformer Networks with Reinforcement Learning for fast and high-quality path planning.	3	59, 101, 134
CP9.5	Use of Mixed-Integer Nonlinear Programming (MINLP) for optimal path planning considering energy and ground vehicle motion constraints.	3	30, 51, 105
CP9.6	Modeling the UAV-load system using a geometric cylinder-cone model to define safety boundaries and clearance for path planning.	2	57, 74
CP9.7	AI algorithms for collision-free, C4-continuous path planning and dynamic re-planning during movement.	2	57, 102
CP9.8	Use of ANN and DRL to enable real-time adaptive path planning in dynamic environments.	2	70, 107
CP9.9	Intelligent Path Planning Algorithm (IPPA) to optimize UAV paths considering loop and no-crossing characteristics.	2	30, 51
CP9.10	Robust optimization considering wind and rain conditions with ML-driven real-time path adjustments.	2	111, 116
CP9.11	Use of off-board computation for path planning and collision avoidance using precomputed LiDAR data.	1	114
CP9.12	Columnar space modeling method combined with a CRO-based algorithm for more precise and efficient path planning.	1	129

Table 19. Limited Battery Life.

S. No	C10 Practices for Limited Battery Life	Frequency	References (Paper ID)
CP10.1	Use hybrid energy supply and energy-aware scheduling to extend flight time.	8	75, 76, 91, 103, 104, 105, 112, 134
CP10.2	Design energy-aware AI algorithms balancing power and performance.	7	34, 76, 91, 103, 104, 112, 134
CP10.3	Deploy edge devices for onboard processing to reduce communication energy.	4	47, 48, 55, 65
CP10.4	Optimize CPU frequency, task routing, and charging strategies jointly.	3	51, 75, 133
CP10.5	Adapt model update frequency to balance performance and energy usage.	3	50, 75, 91
CP10.6	Implement scheduling considering battery constraints and recharging.	2	58, 69
CP10.7	Simplify decision-making logic to improve energy efficiency and endurance.	2	8, 75
CP10.8	Apply GDC-based path planning considering battery and task order.	1	77
CP10.9	Use DRL optimization, federated learning, and wireless energy harvesting.	1	104

demands but may experience reduced prediction accuracy compared to more complex deep learning models. Edge computing architectures improve real-time processing and reduce communication latency by distributing computation across multiple nodes. However, this distributed architecture can increase the attack surface of the system and introduce additional cyber security risks. Multi-sensor fusion techniques improve navigation accuracy by combining data from sensors such as LiDAR, cameras, and inertial measurement units. Although highly effective, these approaches increase the cost of the system, the power consumption, and the complexity of integration. These observations demonstrate that while AI techniques provide significant benefits for UAV systems, their deployment requires careful consideration of trade-offs between accuracy, computational efficiency, scalability, and system security. Understanding these limitations is essential for selecting appropriate solutions for specific UAV applications.

8 Limitation and threat to validity

The study relies on a systematic literature review thus, the findings are subject to the availability, quality, and interpretation of the existing published studies. Despite the structured protocol and several digital libraries, some relevant studies may have been unintentionally overlooked due to variations in terminology, indexing, or publication venue. Specifically, research on AI-based UAV systems spans multiple domains (robotics, networking, control systems, computer vision, and embedded systems), where similar methods are often described using different technical terms. Consequently, the researchers were required to map heterogeneous solutions into homogeneous challenges, which introduces a risk of classification bias. The review was limited to peer-reviewed English-language publications, potentially restricting generalization and excluding industrial reports, non-English studies, or emerging practical solutions not yet published in academia. Moreover, frequency based identification of critical challenges reflects research attention rather than absolute practical significance therefore, frequently studied challenges may appear more important than less-reported but practically critical issues. Another limitation arises from the diversity of experimental conditions across the original studies, including UAV platforms, environments, datasets, and evaluation metrics, which prevents direct comparison of results. The data extraction and screening were conducted systematically by multiple authors to minimize bias however, subjective interpretation cannot be completely eliminated. Additional methodological details and supporting materials are provided in Appendix A. Thus, the findings should be interpreted as a consolidated view of research trends rather than a definitive hierarchy of real-world UAV deployment challenges.

9 Conclusion

This systematic review of the literature focused on the topic of AI integration in UAVs and was guided by two research questions. RQ1 aimed to identify the most significant challenges, and RQ2 explored the solutions/practices that have been suggested to overcome these challenges. To realize this, 141 publications were reviewed without any time limitations to ensure a detailed review of the available knowledge. Ten significant challenges to the implementation of AI in UAV systems were recognized in the review, which are autonomous navigation in complex and dynamic environments, real-time decision-making and emergency response, network and sensor limitations, limited computational resources, poor communication and coordination, high energy consumption, hardware and payload constraints, security and privacy concerns, path planning and collision avoidance, and limited battery life. As a response, more than 100 solutions/practices were identified in the literature, such as lightweight AI model, better communication models, energy-efficient models, and security-enhanced models. Collectively, these results can provide well-organized responses to research questions, highlighting challenges (RQ1) and the wide range of prospective solutions/practices (RQ2). This review is valuable because it can be applied in two different ways. It gives the researchers a methodical overview of the challenges and their solutions/practices, which they may use as a framework for additional research. For practitioners, it offers a list of achievable practices that can be used to guide the design and implementation of powerful AI-powered UAV systems. However, It should be noted, however, that this study has several limitations. The usefulness of the suggested challenges and solutions/practices was not experimentally evaluated, and including all available studies on the issue may have contributed to some old or irrelevant conclusions. Future investigations should focus on empirical validation and comparative assessment of recognized challenges and solutions/practices within actual UAV applications. Furthermore, there is a need to create multidisciplinary solutions/practices that include AI, robotics, networking, and energy systems. Current technologies such as edge computing, federated learning, and renewable energy integration have the ability to solve long standing computational, energy, and security challenges. Lastly, this review presents a general overview of the most essential challenges and solutions associated with the use of AI-based UAVs, highlighting ten major challenges and more than one hundred potential practices. It provides a systematic guide for improving efficiency, security, and resilience within UAV systems. In addition to technological progress, the resolution of these challenges contributes to the more widespread use of UAVs in crucial industries such as military, agriculture, disaster control, environmental surveillance, and supply chain management. Finally, safer and smarter UAV systems have the potential to improve safety, productivity, and reduce operations cost in different industries. Based on identified critical challenges, a number of priority areas of research can be identified. First, the future directions of the research should aim at creating light and energy-conscious AI models that can be used to make real-time autonomous decisions with the limited computational power onboard and limited battery size. Second, there is a need to have effective communication and coordination systems that can facilitate stable multi-UAV and beyond-visual-line-of-sight operations in dynamic environments. Third, AI frameworks that safeguard security and privacy need to be highlighted to ensure reliable implementation and security against cyber threats. Fourth, AI-UAV solutions/practices should be experimented on standardized evaluation benchmarks and realistic validation datasets to improve the reproducibility of results. Lastly, end-to-end architectures uniting edge computing, federated learning, and adaptive energy management are a research gap that awaits research to be accomplished to meet the goal of a scalable and fully autonomous UAV ecosystem.

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