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Review

A Scoping Review of the Crazyflie Ecosystem: An Evaluation of an Open-Source Platform for Nano-Aerial Robotics Research

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Highlights

What are the main findings?

- There are multiple research topics that need to be deployed on reliable open-source aerial platforms, and the Crazyflie nano-drone is a versatile option.
- The Crazyflie ecosystem offers a range of hardware and software capabilities that enable coupling experimental setups with specific research topics and application domains.

What are the implications of the main findings?

- The Crazyflie platform is confirmed as a mature, open-source testbed for experimental aerial robotics research and a highly viable educational tool.
- The synthesis of hardware configurations and thematic trends provides a strategic roadmap for researchers to leverage the platform's capabilities for future innovation.

Abstract

Nano-aerial vehicles have emerged as pivotal tools in modern robotics research, offering a safe and scalable means to validate complex algorithms in resource-constrained environments. This scoping review synthesizes the extensive body of work on the Crazyflie nano-quadcopter and evaluates its potential for drone application development in research and academia. The Crazyflie quadcopter has emerged as a leading open-source platform for education and research in aerial robotics due to its modularity and low cost. Despite its rapid evolution, there is currently no comprehensive synthesis mapping its diverse applications across hardware configurations and research domains. This evaluation systematically charts existing research on the Crazyflie platform, outlining its development, identifying relevant hardware and software configurations, categorizing major research topics, and identifying knowledge gaps. A systematic search was performed on three major databases, Scopus, Web of Science and Google Scholar, for studies published between 2015 and 2025. The results indicate a rapid growth in scientific production, an involved research community and very diverse thematic approaches. Expansion decks for the Crazyflie have been analyzed together with their relation to specific fields of research. While control systems remain the primary research theme, there is a significant shift toward artificial intelligence and swarm robotics.

Keywords: Crazyflie; nano-drone; quadcopter; aerial robotics; UAV; open-source; scoping review

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1. Introduction

The number of applications for unmanned aerial vehicles (UAVs) in various fields has increased significantly in recent years. One of the most popular types of aerial vehicles today is the quadcopter, a drone with four motors and propellers. The four propellers on a quadcopter enable hovering and impressive maneuverability for indoor and outdoor tasks. Having an easy, inexpensive way to test and run diverse experiments is very important for advancing this field and improving research quality and accessibility. Thanks to its low cost, open-source design, and off-the-shelf availability, the Crazyflie platform produced by Bitcraze has emerged as a ready-to-use testbed that facilitates rapid prototyping and lowers the barrier to experimenting with new control, sensing or swarm strategies in both research and educational settings. This type of drone is also an ultra-compact, modular, and fully programmable UAV.

The Crazyflie has been adopted as an educational platform in fields such as robotics, control engineering, and embedded systems. It combines affordability, safety, and sufficient onboard capabilities to expose students to relevant applications of aerial robotics. Because of this, it has become a very popular educational tool used by even top universities worldwide (universities in the top 500 according to the Academic Ranking of World Universities—ARWU). Compared to larger UAV platforms, Crazyflie drones can be flown indoors with minimal safety risks, enabling hands-on experimentation in controlled environments such as classrooms or teaching laboratories. The availability of open-source firmware, well-documented APIs, and a Python-based control interface allows students to interact directly with low-level control loops, state estimation, and sensor data. Another key educational advantage of the Crazyflie platform lies in its modularity and scalability. Expansion decks that use optical flow sensors, localization, and Artificial Intelligence (AI)-based computation modules enable increased system complexity and the adaptation of experiments to different levels and fields of study.

To contextualize the position of the Crazyflie platform for academic and experimental research, it is useful to compare it against other prevalent UAVs in its weight and size class, notably the DJI Tello EDU and the Parrot Mambo. Table 1 presents a technical comparison of these platforms. While the DJI Tello EDU offers superior out-of-the-box flight time (13 min) and an integrated camera, it relies on a closed-source hardware architecture and a black-box flight controller, severely limiting algorithmic modifications. The Parrot Mambo, though highly popular in educational settings via its MATLAB/Simulink support, is largely discontinued with strict payload limitations (approx. 4 g). In contrast, the Crazyflie ecosystem trades off initial flight time for a fully open-source hardware (HW) and software (SW) stack. Its high modularity (via expansion decks) and robust Software Development Kit (SDK) capabilities allow researchers to tailor the platform to their needs.

In parallel with its educational role, the Crazyflie has established itself as a powerful experimental platform for research in aerial robotics and related fields. Its open hardware and software architecture enables researchers to modify controllers, sensing algorithms, and communication protocols. Despite its small scale and limited onboard resources, the platform supports sophisticated experiments in different areas. Moreover, the ability to deploy multiple Crazyflies simultaneously has made the platform particularly attractive for swarm robotics research.

Since their introduction, Crazyflie drones have evolved in terms of hardware, expansion decks, and software ecosystems. The associated literature has also rapidly grown and diversified in scope, methodology, and application domains. Even with this widespread adoption, the literature currently lacks a broad overview detailing the specific ways Crazyflies are utilized across various scientific areas. Furthermore, a systematic look at preferred configurations and existing research gaps has yet to be conducted. To confirm

the absence of existing comprehensive reviews on this specific topic, a targeted search was conducted in Google Scholar, Scopus and Web of Science databases, using the query strings ("Crazyflie" AND "Review") and ("Crazyflie" AND "Survey"). While this search yielded general UAV surveys or platform introductions, no systematic mapping or scoping review dedicated to the Crazyflie ecosystem was identified. Table 2 positions this scoping review against the closest related literature, highlighting the existing gap in comprehensive ecosystem analysis. At the moment, one of the most relevant articles presenting Crazyflie's capabilities is [1], which briefly describes its relevance in the field and its abilities. A survey of aerial robotics simulators is presented in [2] and also mentions some ways in which the Crazyflie can be virtually replicated. More technical specifications of the Crazyflie are present in [3]. This paper also compares it to other UAVs from different technical aspects such as mass, flight time or battery capabilities. Although they approach relevant topics, these articles just briefly discuss some aspects of the Crazyflie environment, but do not grasp the whole scale of it.

Table 1. Technical and platform comparison of popular micro-UAVs used in research and education.

Feature/Metric	Crazyflie 2.1	Crazyflie Brushless	DJI Tello EDU	Parrot Mambo (Discontinued)
Manufacturer	Bitcraze	Bitcraze	Ryze Tech/DJI	Parrot
Open-Source Status	Fully Open (HW & SW)	Fully Open (HW & SW)	Closed HW/Open SDK	Closed HW/Open SDK
Retail Price	~$240	~$480	~$130	~$100–$150
Max Flight Time	~7 min	~10 min	~13 min	~8–9 min
Max Payload	15 g	40 g	~20 g	~4 g
Base Sensors	IMU, Barometer	IMU, Barometer	IMU, Barometer, Downward-facing ultrasonic and optical flow, Camera	IMU, Barometer, Ultrasonic, Downward-facing Camera
Modularity/Hardware	High (Expansion Decks)	High (Expansion Decks)	Low (Mission Pads only)	Moderate (Smart Block)
Supported SDKs/APIs	Python, C/C++, ROS 1/2	Python, C/C++, ROS 1/2	Python, Scratch, Swift	Olympe, Python, MATLAB

By synthesizing multidisciplinary research, we have a more extensive review that fills the existing gap in understanding the practical and theoretical potential of Crazyflie drones, thereby shaping future innovation and research strategies. Within this context, a bibliometric analysis offers a promising way to clarify the field's growth, evolution, and principal collaborations. This also provides a foundation for a scoping review. The methodology of a scoping review allows the inclusion of studies and source types, supports systematic mapping of key concepts and technological aspects, and facilitates the identification of knowledge gaps and future research directions in the rapidly evolving field of the Crazyflie drone environment.

The overall aim of this scoping review is to systematically map the published research that uses the Crazyflie quadcopter platform in robotics and related fields. The first objective is a bibliometric analysis of publication types, institutions, and citations. This scoping review also aims to identify and describe the types of Crazyflie, expansion decks, and positioning systems reported in the literature, and how these configurations are combined in experimental setups. Another topic addressed is the types of software tools and simulation environments used with the Crazyflie. At the same time, the review seeks to summarize

the role of these types of drones in development and experimentation, pinpointing the main research topics and application domains in which they were employed and identifying gaps in knowledge and underexplored combinations of hardware, software, and application areas. The information presented in this paper can inform future research on Crazyflie equipment and also provide educators with an overview of this open-source environment's capabilities.

Table 2. Comparison with existing review articles.

Reference	Primary Focus	Specificity to Crazyflie	Methodology	Contribution
Giernacki et al. [1]	Introduction of the platform and relevance for research and education	High (Focuses only on Crazyflie 2.0)	Platform description	Presents basic capabilities and physical parameters of a single Crazyflie model.
Dimmig et al. [2]	Aerial robotics simulators	Low (Mentions Crazyflie as one of many platforms)	Systematic survey	Compares various UAV simulators; not focused on hardware or real-world applications.
Karahan [3]	Evolution of quadrotors	Low (General overview of different types of UAVs)	Narrative review	Discusses general quadrotor mass, flight times, and battery capabilities across the industry.
This Study	**The complete Crazyflie hardware and software ecosystem**	**High (Exclusively Crazyflie ecosystem)**	**Scoping Review & Bibliometric Analysis**	**Systematically categorizes 321 papers, maps hardware/deck usage, and identifies research gaps.**

The last line (in bold) highlights the work in this study and its uniqueness.

2. Methods

This review was created in accordance with the PRISMA-ScR [4] guidelines. The related protocol followed is presented in the following subsections.

2.1. Search Strategy

The search strategy involved a comprehensive identification of studies on Crazyflie drones across two major databases: Scopus and Web of Science (Clarivate). For the searches, keywords like "Crazyflie" and its derivatives ("Crazyflie 2.0", "Crazyflie 2.1" or "Crazyflie Brushless") were used. The term "Bitcraze", the name of the manufacturer, was another word used for searching papers. For Web of Science and Scopus, all documents since 2015 were considered. This date was chosen because the Crazyflie 2.0 was released in December 2014. The date on which these searches were performed was the 2nd of December 2025. In addition to these two databases, the search was expanded to Google Scholar, specifically to capture the most recent studies and preprints available at the time of extraction, as these are

often not yet indexed by the primary databases. For this database, all records from 14 October 2024 to 15 September 2025 were considered. To keep the search relevant, several fields of study were excluded. The complete search strategy is available as Supplementary Material.

2.2. Study Selection Protocol

After combining these records, duplicate entries were removed first using tools such as Biblioshiny [5] and then manually. To account for the possibility of preprints that have been later published in a journal or at a conference, all preprints have been manually compared to the other entries of the database, and only the most recent version was kept. To import the documents obtained from Google Scholar into Biblioshiny, Dimensions [6] was used to search for articles by Digital Object Identifier (DOI). Because some articles could not be retrieved from Dimensions, they were manually added to the collection. All papers needed to use a Crazyflie drone or derivatives (Crazyflie Bolt) in their experiments or simulations to be considered eligible for inclusion. Theoretical papers were also considered, for example, those that addressed the drone's mathematical model. Although not a common practice when it comes to systematic reviews, no abstract or title screening was conducted because of uncertainty about whether the papers indicated the use of Crazyflies. To be as thorough as possible, even if it means that some papers could have been identified faster, we have opted to analyze the full text of each paper in order to conclude whether it used the Crazyflie drone or not. The language in which they were written was not relevant to the screening process. In addition to peer-reviewed journals and conference articles, preprints were included to capture recent and emerging research.

2.3. Data Extraction

Before extracting data, several manual modifications have been made to the dataset. Some DOI identifiers, abstracts, and affiliations have been added where they are missing. At the same time, the names of sources, authors, and affiliations have been standardized to address minor differences in labeling across publications. The protocol for these manual corrections involved cross-referencing the missing or inconsistent data directly with the original publisher's webpage or the official PDF document of the paper. These modifications will aid in computing statistics and conducting further analyses.

From the resulting documents, data was extracted through several methods. First, a custom Python script was created. For each publication, key characteristics were extracted, including the Crazyflie version used (Crazyflie 2.0, 2.1, Brushless or Bolt), expansion decks (Flow, Z-ranger, Multi-ranger, Breakout, AI, LED-ring, Buzzer, Qi Charger, BigQuad, Micro SD Card, Prototyping, or a custom one), or what type of positioning system was used (Loco Positioning, Lighthouse or another motion capture system based on markers). The script also searched for a specific simulation environment (Gazebo, Webots, CrazySim, Sim_CF2, CrazyS, Crazyflow, Gym PyBullet, or RViz) or for the use of Robot Operating System (ROS) or Crazyswarm. The script prompts the user with a paragraph containing keywords, and the user can accept or reject them, enabling a manual rejection and approval system. The keywords were not accepted automatically using a script alone to avoid, for example, cases where a sensor was mentioned in the paper but not actually used in the experiments. When information was ambiguous or insufficiently described, the study was manually flagged by the user for further review, and the entire text was examined. The specific regular expressions used for each information are present in the script available at [7]. The extracted data was organized in a tabular format to facilitate data analysis and the computation of relevant statistics, such as the number of papers that used each Crazyflie version, expansion deck, or simulation environment.

Secondly, the R-based application Biblioshiny was employed. Biblioshiny is an interactive web application designed to facilitate the visualization and analysis of bibliometric data. It enables users to explore publication trends, author collaborations, keyword co-occurrences, and citation networks through dynamic and customizable graphical interfaces. In the context of this scoping review, Biblioshiny was employed to analyze characteristics of the included studies such as publication years, sources of publications, number of citations, institutions, authors and keywords.

Manual analysis was performed primarily from the abstracts and, when necessary, from the full texts of the articles. The data charted after this examination is a classification of the papers by the field that the research was focused on, which would be one of the following: Control Systems and Flight Stabilization, Autonomous Navigation and Obstacle Avoidance, Swarms and Multi-Agent Systems, Monitoring, Inspection and Environmental Applications, Sensing, Localization and Sensor Fusion, Safety-Critical Applications and Security, Artificial Intelligence Applications or Simulation and Development Tools.

3. Results

3.1. Study Selection

The process of identifying the relevant studies is presented in Figure 1. The number of records returned by the Scopus query was 239 documents, while the output from Web of Science consisted of 208 papers. From Google Scholar, a total of 132 manuscripts resulted. Duplicate removal eliminated 219 records before screening. After removing duplicate entries, all 360 records were sought; however, 21 reports were not retrieved. An eligibility assessment was conducted on 339 reports, excluding 18 studies that did not use a Crazyflie drone. Ultimately, 321 studies met the inclusion criteria and were incorporated into the review.

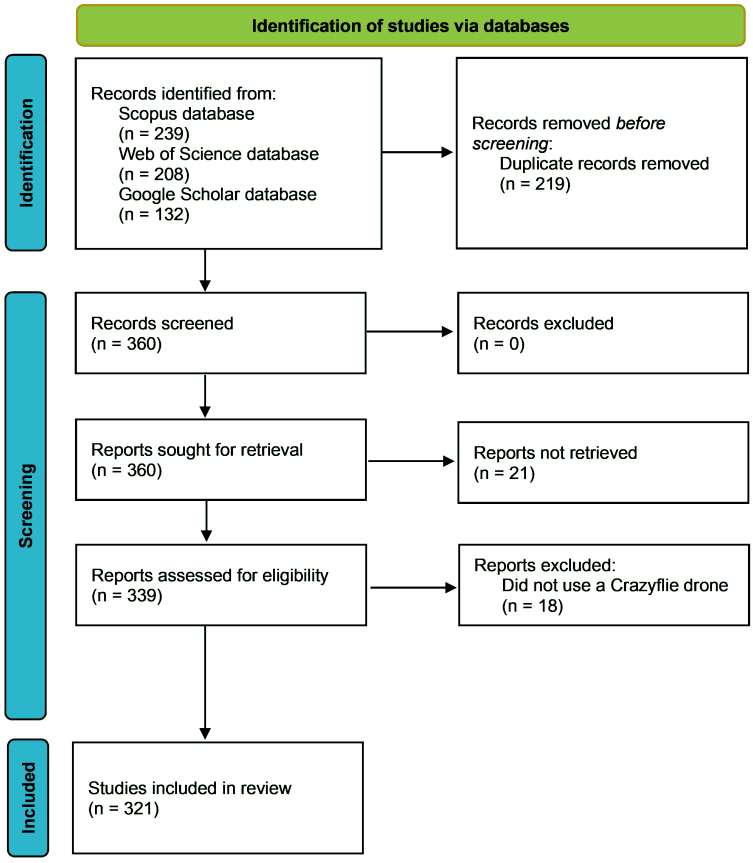


Figure 1. PRISMA flow diagram for our work. Adapted from [8].

3.2. Study Characteristics

The following analysis provides a snapshot of the research collection gathered. It spans from 2015 to 2025. Regarding missing information in the documents, there are a few notable mentions. The absence of Cited References from this collection is a known limitation of the merging process, as it will affect citation-based analyses beyond the per-document average. There are 165 Keywords and 205 Keywords Plus that are not present in the metadata. At the same time, four papers lack an affiliation, and 20 lack the journal in which they were published.

The research is disseminated across 183 distinct publication venues. The sources with the most documents are presented in Figure 2.

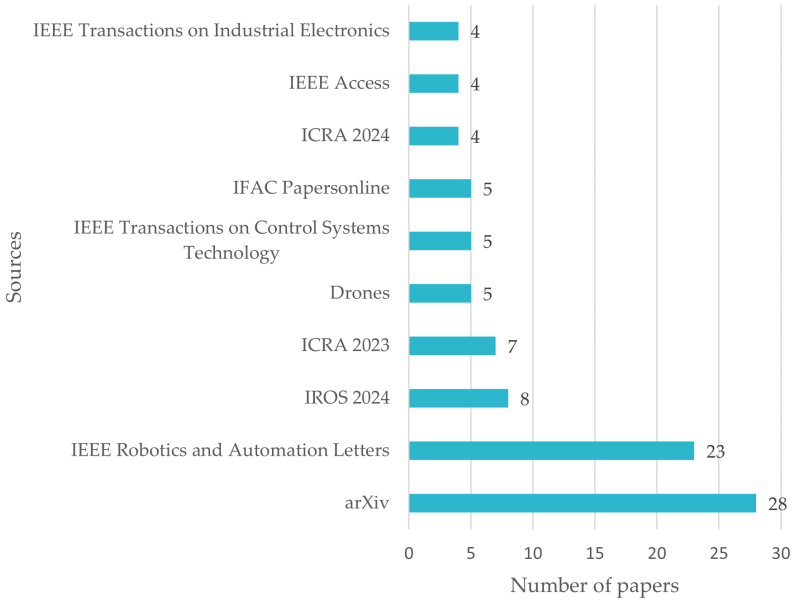


Figure 2. Most relevant sources of the extracted papers.

The annual growth rate of 38.87% is exceptionally high. It strongly indicates a rapidly expanding field of research that has seen a significant surge in interest and output over the past few years. An evolution of the scientific production can be visualized in Figure 3. This graph reveals a period of stagnation followed by a sharp increase. Between 2015 and 2021, activity remained relatively low and stable, fluctuating between 0 and 16 publications. A significant shift occurred in 2022, when the number began to rise sharply, reaching 46 in 2023. This upward momentum peaked in 2024, with a high of 105 documents. However, the trend shows a downturn in 2025, dropping to 80 documents. It is to be noted that any material published after 2 December 2025, the date at which the data was last extracted, was not taken into account for this graph. Although there is a drop, this figure remains significantly higher than the historical average seen prior to 2023, showcasing persistent interest in Crazyflie research.

There is a mix of document types for papers that use the Crazyflie, as shown in Figure 4 as percentages. The number of conference proceedings papers (154) suggests a significant reliance on this publication type for disseminating research. Traditional journal articles are also a significant output, totaling 108. The presence of 31 preprints underscores the desire for rapid dissemination of research findings. The remaining document types (e.g., book chapters) are minor contributors.

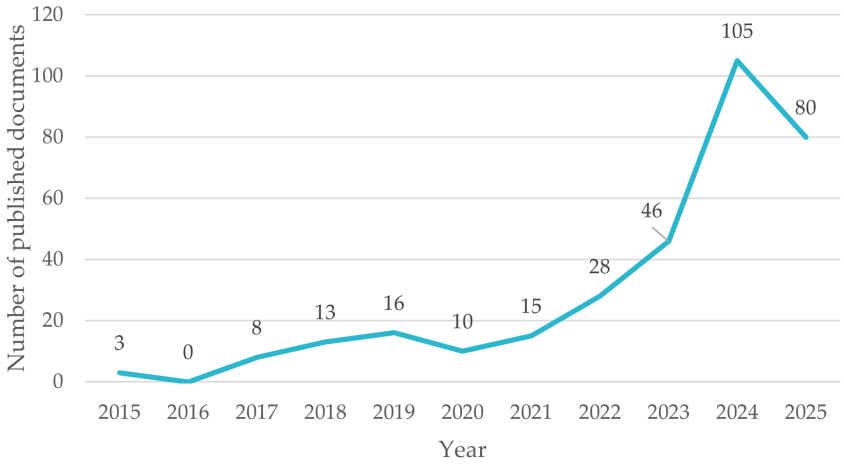


Figure 3. Annual scientific production from 2015 to December 2025.

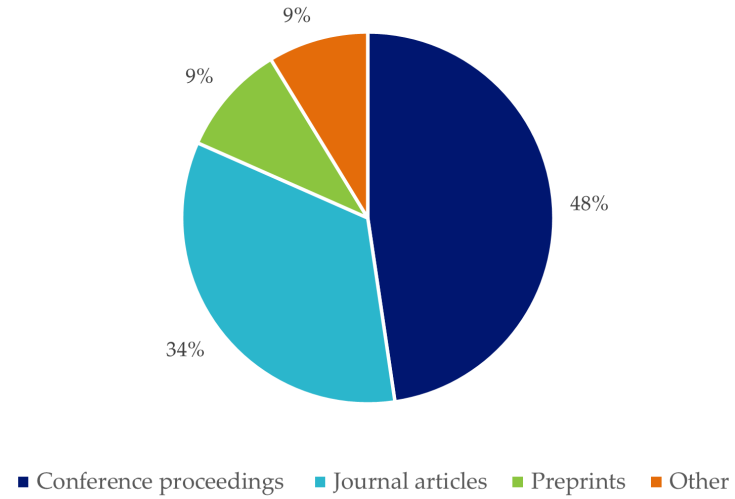


Figure 4. Distribution of publication types.

The average document age is 3.07 years. Many papers are still new and have not had enough time to accumulate many citations. An average of 6.34 citations per document suggests that the published research is being noticed and cited by other scholars relatively quickly, considering the age of the published material.

Table 3 shows the most cited papers that use the Crazyflie drone, taking into consideration only the number of citations from the Web of Science database. The Normalized Citation score of a document is calculated by dividing the actual count of citing items by the expected citation rate for documents with the same year of publication. It is noteworthy that in this pool of most relevant papers, there is a mix of both journal and conference papers, indicating that both can achieve high visibility in this field. Another relevant aspect is the diversity of topics addressed by these highly cited works, ranging from low-level control and state estimation to multi-drone coordination, mixed reality, and autonomous navigation. This variety indicates that the Crazyflie platform is not limited to a single niche but rather supports a broad spectrum of research problems and produces high-quality research. The paper titled "Crazyflie 2.0 quadrotor as a platform for research and education in robotics and control engineering" stands out as the highest cited work with 145 citations. It is also the third-highest in total citations per year, making it a very relevant paper, especially given its 2017 publication. Beyond the leading work by Giernacki et al., the table highlights several other influential Crazyflie-based contributions that are highly cited. For

example, Palossi et al.'s "A 64-mW DNN-based visual navigation engine for autonomous nano-drones" is not only second in total citations but also ranks among the highest in normalized citation score and citations per year.

Table 3. Most cited papers.

Title	Authors	Year	Journal/Conference	TC [1]	TC per Year	Normalized TC
Crazyflie 2.0 quadrotor as a platform for research and education in robotics and control engineering [1]	Giernacki W. et al.	2017	Int. Conf. on Methods and Models in Automation and Robotics (MMAR)	145	16.11	4.48
Low-level control of a quadrotor with a deep model-based reinforcement learning [9]	Lambert N. O. et al.	2019	IEEE Robotics and Automation Letters	123	17.57	4.62
A 64-mW DNN-based visual navigation engine for autonomous nano-drones [10]	Palossi D. et al.	2019	IEEE Internet of Things Journal	119	17.00	4.47
Mixed reality for robotics [11]	Hönig W. et al.	2015	IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS)	107	9.73	2.61
Mixed reality and remote sensing application of an unmanned aerial vehicle in fire and smoke detection [12]	Esfahlani S. S.	2019	Journal of Industrial Information Integration	54	7.71	2.03
Planning, fast and slow: A framework for adaptive real-time safe trajectory planning [13]	Fridovich-Keil D. et al.	2018	IEEE Int. Conf. on Robotics and Automation (ICRA)	44	5.50	2.21
Learning-based bias correction for time difference of arrival ultra-wideband localization of resource-constrained mobile robots [14]	Zhao W. et al.	2021	IEEE Robotics and Automation Letters	42	8.40	3.17
An open source and open hardware deep learning-powered visual navigation engine for autonomous nano-UAVs [15]	Palossi D. et al.	2019	IEEE International Conference on Distributed Computing Systems	37	5.28	1.38
Distributed time-varying optimization with state-dependent gains: algorithms and experiments [16]	Sun S. et al.	2022	IEEE Transactions on Control Systems Technology	36	9	4.93
Optimized L1 adaptive controller for trajectory Tracking of an indoor quadrotor [17]	Jafarnejadsani H. et al.	2017	Journal of Guidance, Control, and Dynamics	36	4	1.11

[1] TC = Total Citations.

3.3. Institutions and Authors

The most prolific institutions in regard to the number of papers published are presented in Figure 5. The graph displays only institutions with at least six publications in

the analyzed dataset. The data highlights ETH Zurich as the primary contributor with 20 publications, followed by a cluster of others, including the University of Bologna (11), Delft University of Technology, Università della Svizzera italiana, Tsinghua University, and the University of Toronto (9).

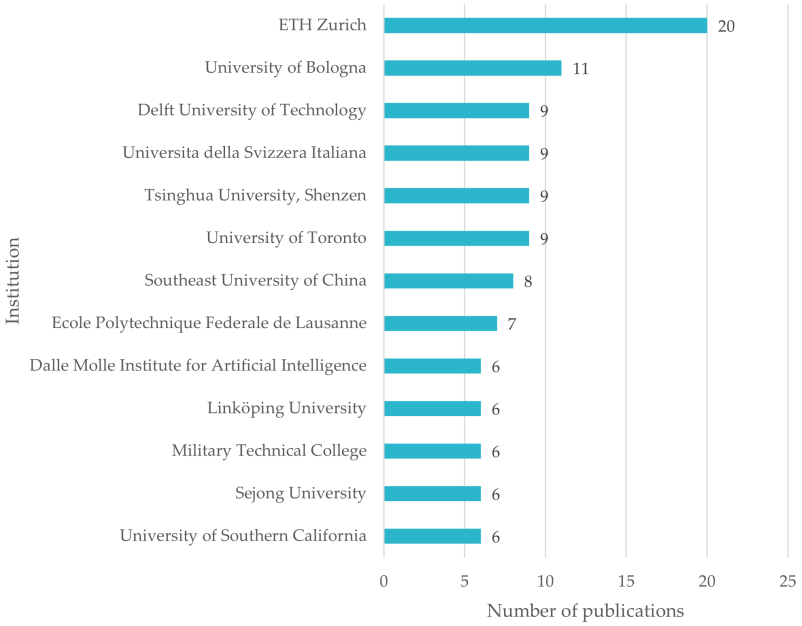


Figure 5. Most relevant affiliations of the authors.

Research in this domain is predominantly conducted by teams rather than individuals. The extremely low number of single-authored documents (only three out of 315, or less than 1%) further reinforces the strong culture of team-based research within this field. The collaboration between authors is high domestically, with authors from the same country cooperating on research papers. The percentage of international co-authorships is relatively low, at just 4.012%. This suggests that the primary collaborative networks are likely national or regional, rather than globally distributed.

The total number of authors extracted from the metadata is 1049. The real number could be lower due to the fact that many author names appear with slight differences across the database. The network in Figure 6 shows co-authorship relationships, where nodes represent authors and edges indicate collaborations on at least two publications. The size of the nodes is proportional to the author's collaboration activity, and edge thickness reflects the strength of the collaboration.

The network is sparse, with large spaces between clusters. This indicates that a significant proportion of authors in the dataset do not collaborate. Many communities consist of only two authors, representing very focused, often one-to-one, research partnerships. There are a few other, more substantial clusters (red, green, orange, purple, or light blue), indicating more extensive collaboration networks around key figures. The red cluster is the most extensive and densely connected cluster, centered around Benini L. It includes authors such as Polonelli T, Niculescu V, Magno M, and Mueller H, all from ETH Zurich. The members of these clusters stand out as the central and most connected authors in the entire network. There is also another very important network formed around collaborators from Dalle Molle Institute of Artificial Intelligence, a joint institute of the Universita della Svizzera italiana and the University of Applied Sciences and Arts of Southern Switzerland, with authors like Palossi D, Crupi L, Giusti A and Conti F.

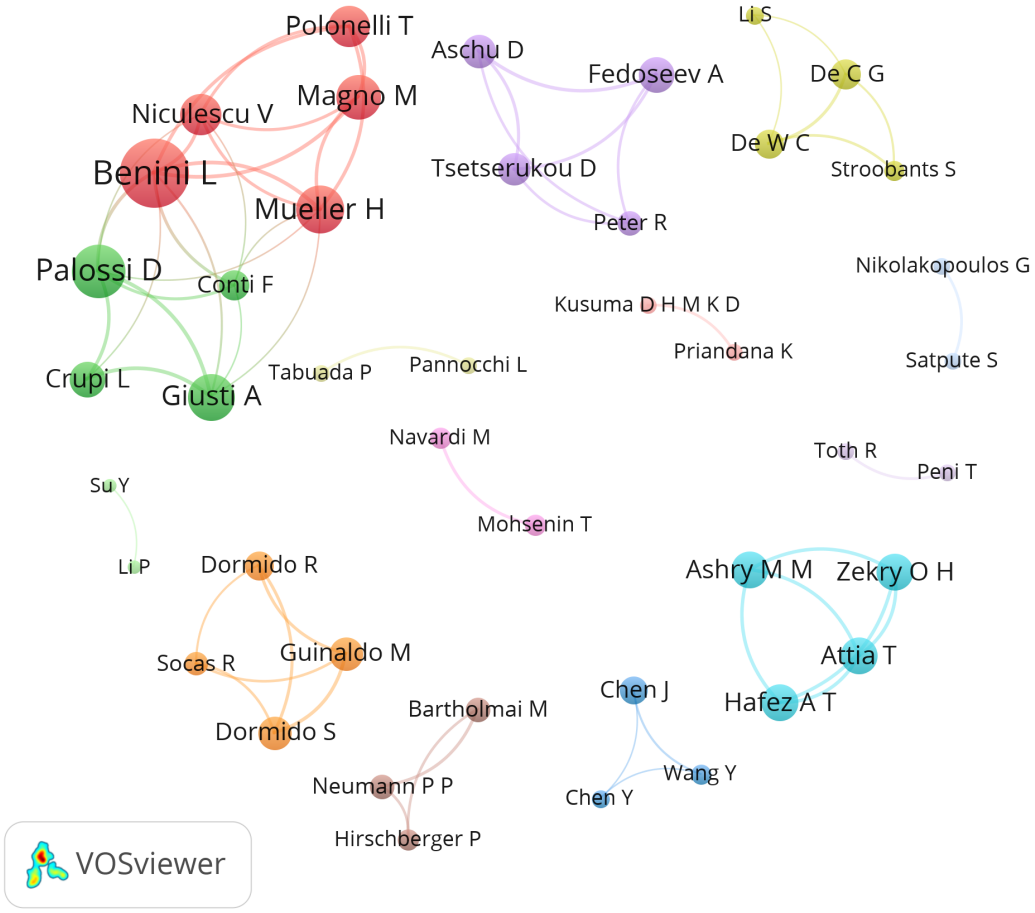


Figure 6. Network of authors that collaborated on at least two publications.

3.4. Thematic Analysis

The most relevant keywords are plotted in Figure 7, along with the number of times they were mentioned. Because of the number of missing author keywords from the database, the plot was created by selecting the groups of one, two and three words from the abstracts of the papers that appeared the most. The list was refined by removing irrelevant words and by merging words or groups using a list of synonyms. The lists are available in Tables S1 and S2.

The word with the most mentions is "control", a very general term that can refer to controlling the Crazyflie's movement in an environment or to control algorithms. "Crazyflie" is, as expected, another keyword with a high number of appearances. The data also reveals a strong focus on both "simulation" (139) and practical implementation, as evidenced by high counts for "experiment" (223) and "real" (193). Using swarms, avoiding obstacles, and tracking trajectories are other topics of interest for the Crazyflie. Furthermore, emerging methodologies such as learning-based approaches, neural networks, and reinforcement learning are being used in research.

Figure 8 presents a graph with connected keywords that appeared in the abstracts of the papers. In this graph, only two word groups have been considered. The keyword network highlights how Crazyflie research tackles incredibly diverse fields, from basic control to intelligent, application-driven aerial robotics, with the Crazyflie quadcopter at the center, connecting several dense thematic clusters. One major cluster groups control systems, PID and MPC control, trajectory tracking and tracking errors, reflecting the strong emphasis on flight stabilization and precise motion control reported in the review. Another cluster links reinforcement learning, neural networks, deep reinforcement learning, and

obstacle avoidance, capturing the growing use of learning-based methods for autonomous navigation and safety guarantees in dynamic environments. Additional clusters connect positioning systems, motion capture, Loco and Lighthouse decks, and experimental results, showing how high-precision localization and real-world experiments underpin much of the Crazyflie work. Peripheral yet important nodes, such as drone swarms, multi-agent systems, and formation control, showcase how the platform scales to coordinated behaviors, while terms like energy efficiency and computation time reflect increasing attention to resource-constrained onboard processing. Overall, the network depicts a research landscape in which modular hardware (expansion decks), advanced control, and machine learning converge around the Crazyflie platform to support a wide range of experimental and simulation-based studies.

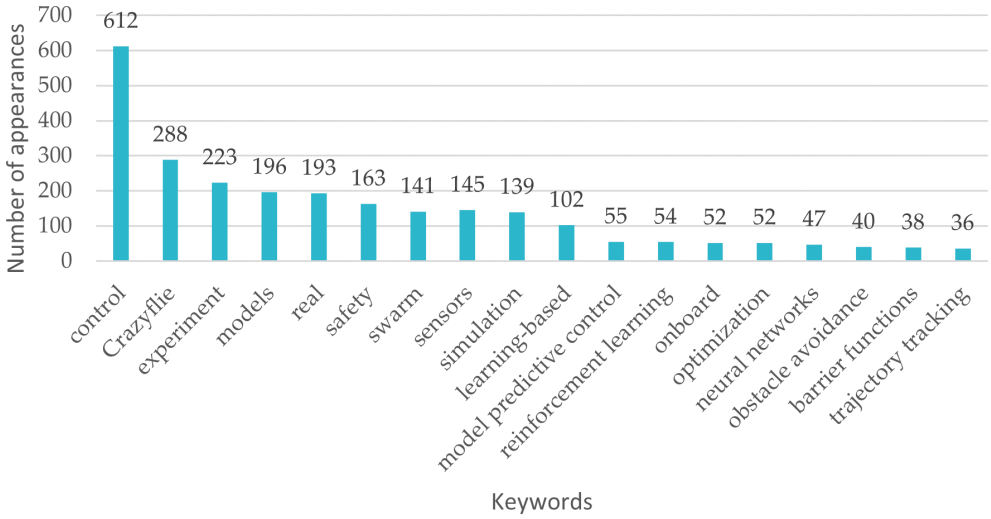


Figure 7. Most frequent keywords extracted from the abstracts.

The evolution of the most significant topics tackled by the articles in the database is presented in Figure 9. This graph provides a clear overview of the evolution of research themes. Only words that have appeared at least 10 times have been visually represented. The bubble is plotted at the median of the interval, with its size determined by the number of appearances. The black lines represent the spread of the data, the left and right whiskers being the first and third quartiles. The visualization highlights how the studies using Crazyflies have progressively shifted from simple technologies toward more advanced, intelligent, and safety-aware aerial robotic systems. It should be noted that there might be a bias in the high number of appearances in the year 2024, as it is the year with the most published material. In the earlier years of the timeline, between 2018 and 2019, research primarily emphasized new technologies for the Crazyflie. The prominence of terms such as ROS, ultra-wideband, and control algorithms suggests that much of the work during this phase focused on establishing reliable software frameworks and control architectures. Around 2022, the field expands further into perception and mapping applications. The appearance of terms such as sensors, cameras, mapping and motion capture indicates a strong reliance on localization and environmental understanding. In recent years, from 2024 to 2025, the plot reveals a shift toward higher-level autonomy and safety. Emerging terms such as convolutional neural networks, model predictive control, control barrier functions, and safety filters point toward the importance of learning-based perception, control, and safety.

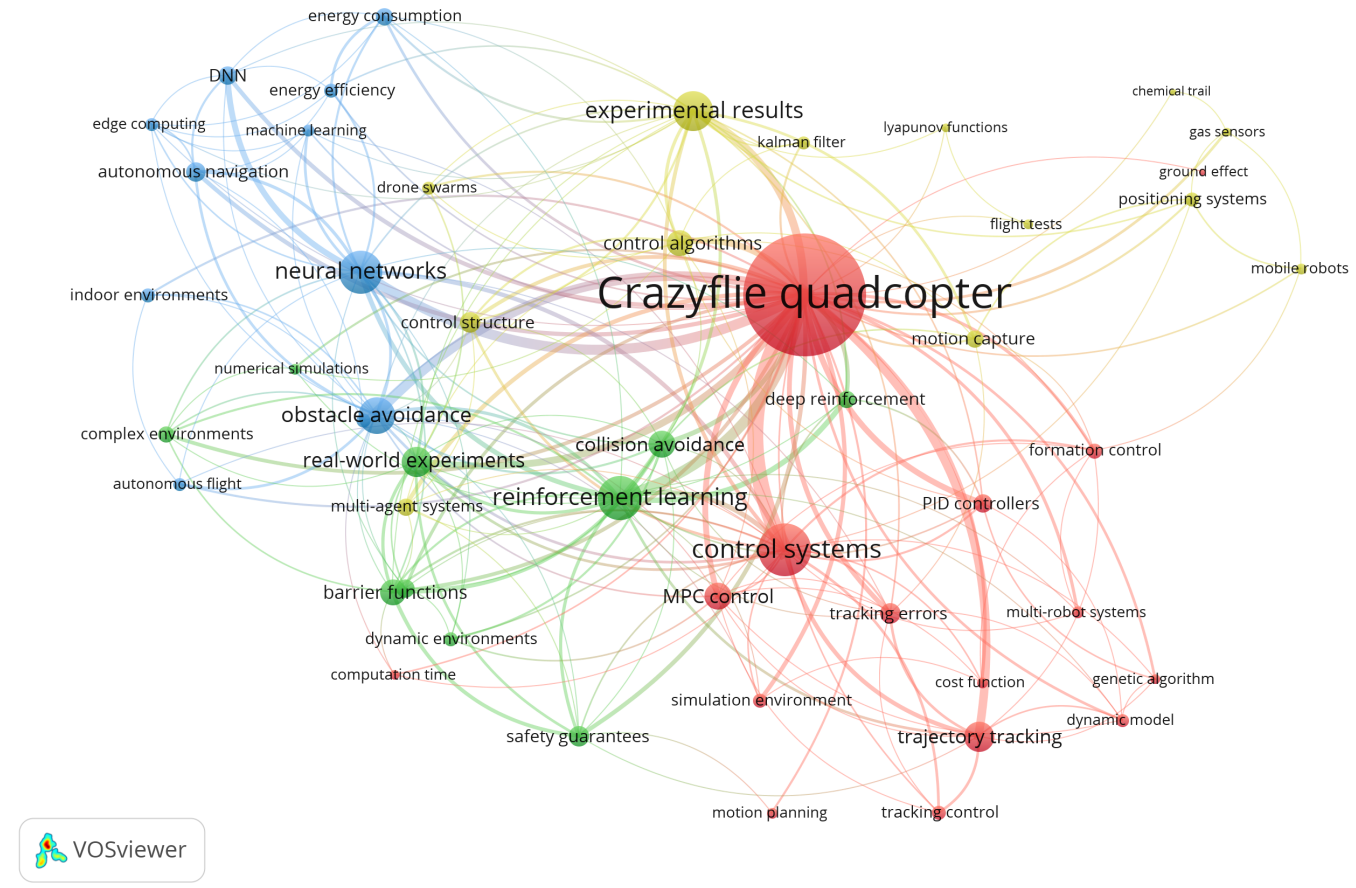


Figure 8. Keyword graph network.

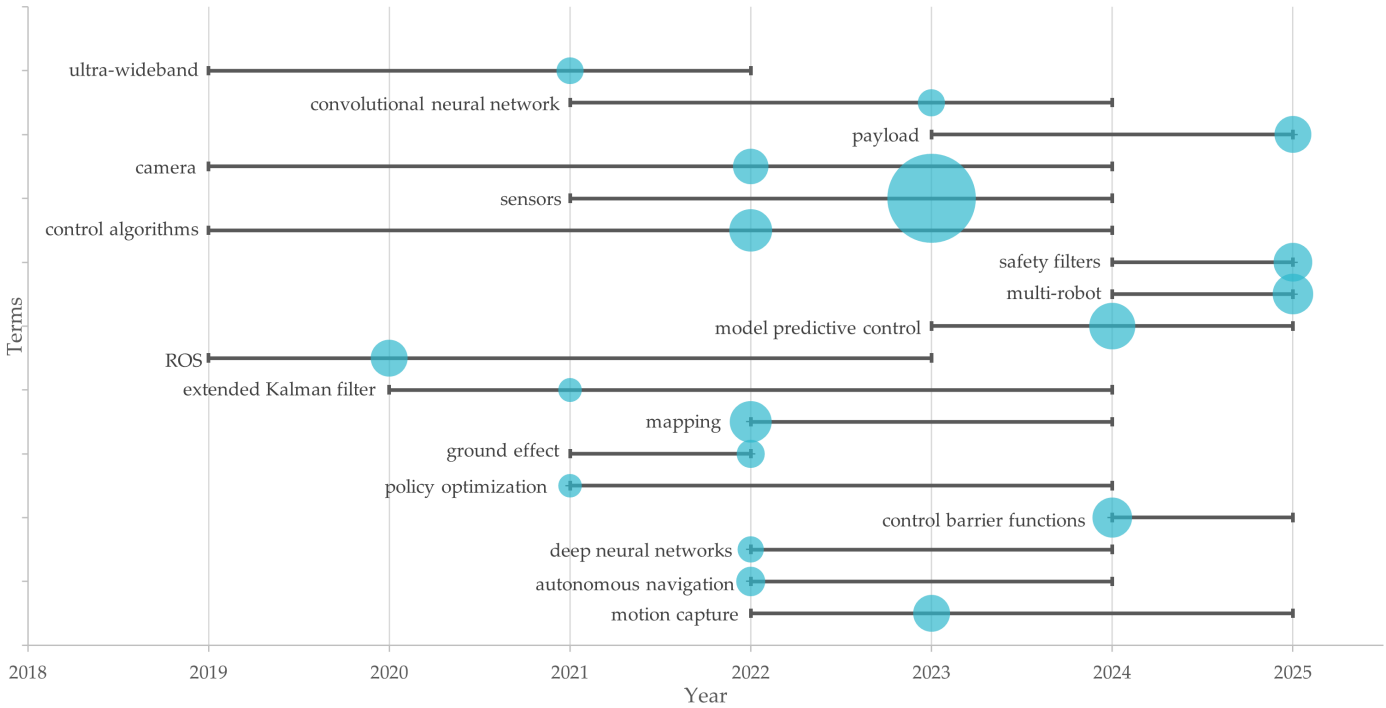


Figure 9. Trend of research topics over the years.

3.5. The Crazyflie Development Environment

The Crazyflie quadcopter is a very small type of drone. Depending on the source, drones can be categorized in several ways, as described in [18], including by wing span,

weight, or flight range. Most of the papers this review analyzed referred to the Crazyflie as a nano-drone or nano-UAV almost three times as often as the term micro-drone. There are also a few mentions of mini-drone, but it is negligible in terms of appearances compared to the other two. This information seems to show a consensus, to a certain degree, on what category the Crazyflie lies in, the nano-drone.

Both the software and hardware are open source. The firmware is based on the FreeRTOS operating system. The default software for the Crazyflie is the Crazyflie Python Client (CFclient), written in Python, which allows real-time viewing of flight parameters and other indicators. The Crazyflie library (CFLib) is a Python-based API designed for interacting with the Crazyflie. It serves as a tool for client software to establish communication and control for a Crazyflie quadcopter. There are currently two actively supported link implementations for the Crazyflie communication protocol: one via radio and one via USB. For remote computer connection, a Crazyradio antenna [19] can be used.

3.6. Crazyflie Versions

The Crazyflie drone has undergone several model changes through the years, but the main equipment, sensors, and capabilities have remained almost the same for all models. The three models that have been analyzed in this review are the Crazyflie 2.0 [20], 2.1 [21], 2.1+ [22] and the 2.1 Brushless [23]. The 2.1+ and the Brushless versions are depicted in Figure 10a and Figure 10b respectively. Of these, the Crazyflie 2.0 and 2.1 are currently discontinued.



(**a**) (**b**)

Figure 10. (**a**) The Crazyflie 2.1+. (**b**) The Crazyflie Brushless.

On all models, the main processing unit on board is a 32-bit ARM STM32F405 Cortex-M4 microcontroller running at 168 MHz. In addition, the drone has a 32 MHz nRF51822 microcontroller for radio communications and power management. In addition to radio communications, the vehicle is equipped with Bluetooth LE. The equipment on board all drones also includes a gyroscopic sensor, an accelerometer, and a high-precision pressure sensor. All the 2.0, 2.1 and 2.1+ versions have a calculated frame size from motor to motor of only 92 mm and a height of 29 mm, while the 2.1 Brushless has a frame 8 mm larger.

There are also some hardware differences between the models. The 2.0 version was equipped with a magnetometer. The 2.1 came equipped with improved IMU and pressure sensors compared to the 2.0 model, but it was 2 g heavier, bringing the total to 29 g. It also came with better radio performance and antenna support and a new, more durable power button and cable fastening system. The 2.1+ has just a few slight improvements over the simple 2.1. The drone now has the 47-17 propeller type [24], which enables longer flights and a thrust increase of up to 15%. Another improvement to the battery was made at this

stage. The 240 mAh battery of the previous versions has been replaced with a 250 mAh battery that is also 1 g lighter.

The 2.1 Brushless introduced several significant changes. First, the brushed motors were replaced with brushless motors. The drone is also equipped with a bigger 350 mAh battery and custom propellers and propeller guards. All these improvements result in a longer flight time of 10 min, compared to 7 min in previous versions, and a larger payload capacity of 40 g, more than double the 15 g of other Crazyflie models.

The Crazyflie Bolt [25] is designed as a Crazyflie 2.X compatible flight controller specifically for brushless builds. These components can be used to scale up projects, intended for larger quadcopter platforms with higher lifting capacity and extended flight time. It uses the same firmware binaries and sensors as the Crazyflie 2.1. At the time of writing, the Bolt is still considered "Early Access" by the producers, meaning that although the hardware is finalized, the software component still needs development.

The total number of papers that have used each type of Crazyflie is presented in Table 4. Due to the many similarities and sometimes indistinguishable differences between the 2.1 and 2.1+ versions, they have been counted as the same item in the table. From the rest of the papers, there was no mention of a certain model of the drone. The leader in appearances is the Crazyflie 2.1/2.1+, which has been used in 112 studies, followed by the 2.0 with 66. The low number of papers that used the Crazyflie Brushless may be due to the version being relatively new at the time the documents were collected, less than a year old.

Table 4. Crazyflie drone versions used.

Type of Drone	Number of Appearances
Crazyflie 2.0	68
Crazyflie 2.1/2.1+	115
Crazyflie Bolt	6
Crazyflie Brushless	1

3.7. Mathematical Models of the Crazyflie

Essential to controlling a drone is knowing the kinematic or dynamic model of the vehicle and also how it is controlled and stabilized. Several papers have tackled the mathematical model of the Crazyflie drone to better understand its kinematics. A summary is presented in Table 5.

Table 5. Comparison of mathematical modeling approaches for Crazyflie.

Reference	Crazyflie Version	Model Type	Key Assumptions	Advantages	Limitations
Luis & Ny [26]	Crazyflie 2.0	State-Space (Euler Angles)	Rigid body, symmetrical structure, center of gravity at origin	Intuitive physical representation; Detailed parameters and system identification steps; Validated in simulation and real-life experiments	Subject to gimbal lock; Ignores aerodynamic effects.
Zekry et al. [27]	Unknown	Non-linear State-Space (Euler Angles)	Symmetrical structure	Comprehensive non-linear representation	No limitations are mentioned

Table 5. *Cont.*

Reference	Crazyflie Version	Model Type	Key Assumptions	Advantages	Limitations
Greiff [28]	Crazyflie 2.0	Linear and non-linear State-Space (Euler & Quaternion)	Rigid body, rotor and rigid-body dynamics decoupled; Thrust is proportional to the rotor speed	Includes drag effects in modeling; Quaternion avoids gimbal lock; Quaternion state-space form is optimized for real-time embedded execution	Subject to gimbal lock (Euler); Diminished controllability (Quaternion)
Lee et al. [29]	Crazyflie 2.1	Non-linear Quaternion dynamic model	Thrust is proportional to the rotor speed	Avoids gimbal lock; Reduced computational time	No limitations are mentioned
Förster [30]	Crazyflie 2.0	Parameter Identification (rigid body inertia, motor transfer function, and aerodynamic drag models)	Symmetrical structure, center of mass is the same as the geometrical center; Small-angle assumption $\sin(\varphi) \approx \varphi$; Motor angular velocity is assumed to be zero for input commands below 1000	Provides exact physical parameters (inertia matrix, thrust-to-torque ratio) obtained experimentally	Inertia matrix: The friction could be analyzed in more depth; Motor parameters: a load cell with lower resolution and noise was used; The wind generator could be improved to provide a more homogeneous stream of air for better accuracy of drag coefficients.

Most papers, such as [31–34], cite [26] as their source for the Crazyflie's mathematical model. In [26], the authors present the thorough process of mathematically modeling the Crazyflie 2.0. The results present both a linear and non-linear state-space model, both based on Euler angles. Another non-linear state-space model based on Euler angles is derived in [27], this time for an unknown version of Crazyflie. The work in [28] presents both a roll, pitch and yaw and a quaternion-based model for the Crazyflie 2.0. A quaternion model is also derived in [29], this time for a Crazyflie 2.1.

Another study that analyses some physical parameters of the Crazyflie 2.0, as mentioned in papers from the examined database, is [30]. In this study, the coefficients of the inertia matrix, which map motor input commands to the resulting thrust, torque, and rotor angular velocities, are identified. Additionally, a transfer function for the motors was developed, and the drone's drag coefficients, which describe the forces acting on the spinning propellers as the quadcopter moves through the air, were determined.

3.8. Crazyflie Expansion Decks

Modular enhancement of the Crazyflie is achieved through expansion decks that augment the platform's sensing, positioning, and visualization subsystems. The architecture supports both a comprehensive ecosystem of off-the-shelf decks and user-defined hardware. At the time of writing, the producers offer pins with a length to support a maximum of three decks per drone. These decks are compatible with all models after the Crazyflie 2.0, except for the Crazyflie 2.1 Brushless and the LED-ring deck.

An overview of the use of expansion decks in the analyzed literature is shown in Table 6. A full list of expansion decks used in each paper is available as Supplementary Material in Table S3.

Table 6. Available Crazyflie expansion decks.

Sensor	Number of Appearances
Motion capture marker/Active marker	159
Loco Positioning	55
Lighthouse Positioning	38
Flow deck	54
Z-ranger	9
Multi-ranger	17
AI deck	33
Micro SD card	7
QI charger	2
Breakout	1
Custom deck	22
LED-ring	0
Buzzer	0
BigQuad	0

One of the first categories of expansion decks is the positioning decks. Crazyflie drones use several main positioning methods for autonomous flight: external motion capture (e.g., Vicon, OptiTrack, etc.), Lighthouse (e.g., SteamVR) for high-precision and Loco Positioning System (UWB radio) for flexible indoor tracking. The Flow deck also aids in the approximation of the positioning with relative movement and height measurements. The first category uses a motion capture system with cameras and active or passive markers mounted on the drone. This method has been preferred for 158 of the papers analyzed. The motion capture marker deck enables the mounting of reflective motion capture markers that can be detected by infrared cameras, as seen in Figure 11a. The active marker deck is created to be used with Qualisys QTM, but can be re-programmed for different applications and supports up to four different marker IDs. All the calculations for the estimations are done by an external system and then fed to the Crazyflie via a Crazyradio. The precision of estimation for these methods depends on the motion capture system used, but is most often under 1 mm [35]. The biggest disadvantage of this type of system is its price, which is the highest of the three available.

Another module that aids in the localization of the Crazyflie is the Loco Positioning System (Figure 11b), which is based on Ultra Wide Band (UWB) radios. This type of system has been used in 52 papers across the database. The references on which this system is based are a set of anchors installed in the work environment. These anchors are called Loco Positioning Nodes. The other part of the system is represented by one or more tags in the form of the Loco Positioning decks. These tags are attached to the drones that need to be tracked. Depending on the mode used, it is recommended to place six or eight anchors in the room for optimal accuracy. Pose and position estimation is done on board the Crazyflie, enabling an autonomous system without external aid. The accuracy of this system is claimed to be in the 10 cm range [36].

The last system used for the Crazyflie's position computation is the Lighthouse positioning system (Figure 11c), composed of the Lighthouse positioning deck and Lighthouse base stations. The base stations can be either HTC Vive (Lighthouse V1) or SteamVR 2.0 (Lighthouse V2). For the system to work best it is recommended to have two base stations. As with the Loco Positioning System, all the information required for position is available directly on the deck, allowing the position to be estimated right on board the Crazyflie drone without the help of an external computer. The precision of this system, depending on where the drone is in the working space, ranges from a millimeter to a few centimeters at the extreme corners of the space [37].

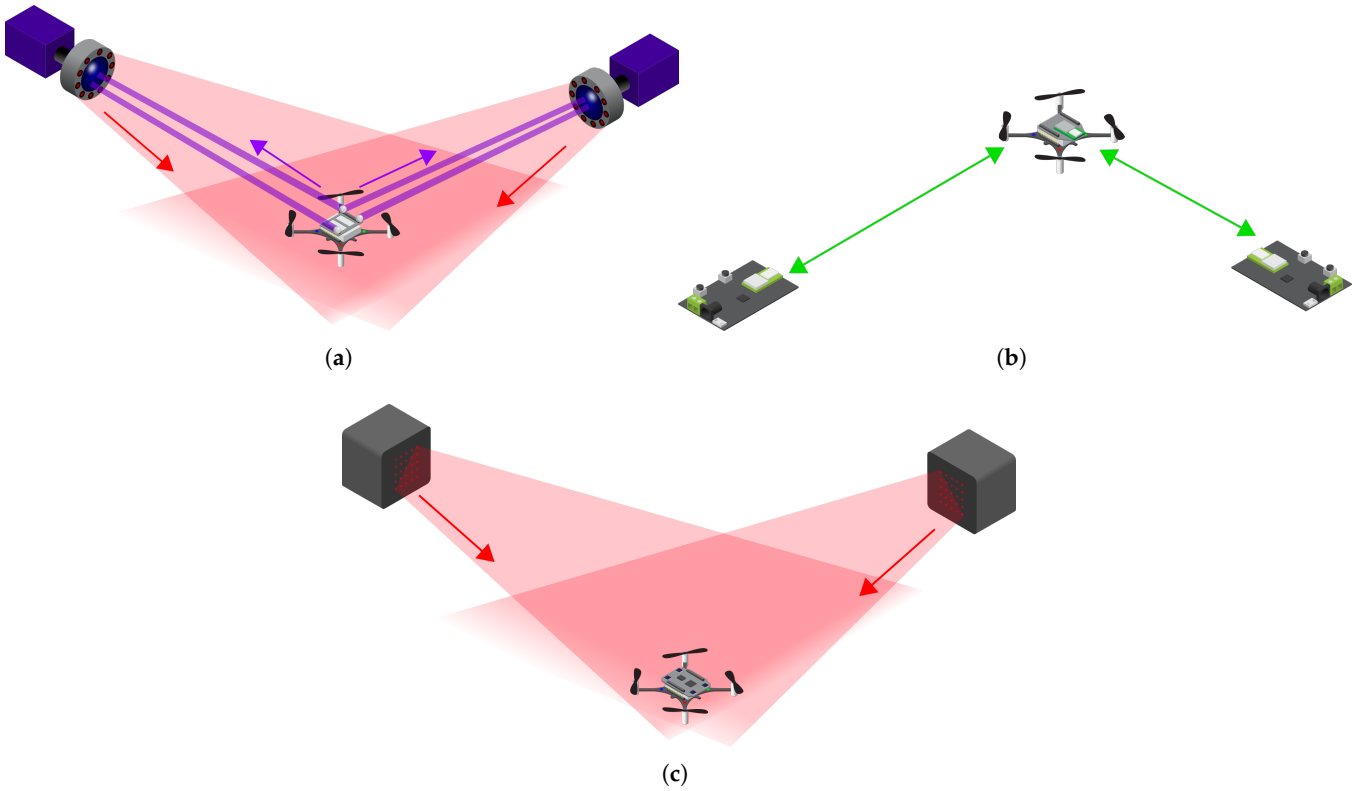


Figure 11. Positioning systems: (**a**) motion capture system (e.g., OptiTrack, Vicon); (**b**) Loco Positioning System; (**c**); lighthouse positioning system.

There are also other types of decks that aid in the estimation of the positioning of the Crazyflie or are used for calculating distances. As presented in Table 6, the most used deck in this category is the Flow deck (Figure 12a) with 51 appearances. This deck is equipped with a Time-of-Flight (ToF) sensor that measures distance to the ground and an optical flow sensor that measures motion relative to the ground. These sensors enhance the Crazyflie's ability to understand how it is moving. A very similar deck is the Z-ranger, which uses the same laser sensor as the Flow deck to measure the distance to the ground, but lacks the optical flow sensor, making it a less reliable option for estimation, a fact that is confirmed by the low number of papers (9) that used it. The Multi-ranger deck gives the Crazyflie the capacity to measure distances to objects around it in five directions: front, back, left, right and up. This is done through the same ToF sensors as on the Flow and Z-ranger decks.

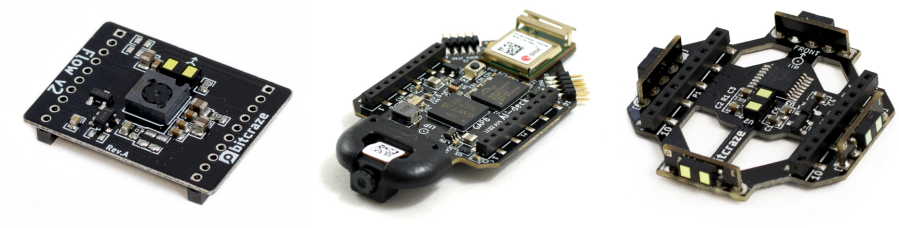


Figure 12. (**a**) Flow deck. (**b**) AI deck. (**c**) Multi-ranger deck.

The AI deck, represented in Figure 12b, adds great computational power to the small drone and better environment sensing capabilities with the mounted camera on it. This deck comes with a GAP8 IoT application processor, an ESP32 that provides WiFi connectivity and a greyscale Himax camera module. This deck has been used in 33 studies across the database. A Micro SD card deck can be used, although it is not a very popular option, as shown in Table 6, if there is a need to save data at a higher rate than the normal radio

transfer. This deck provides speeds up to 1 kHz, ten times that of a radio link, making it suitable for high-speed logging. Other decks that have been used are the Qi charger deck, used for wireless charging the drone, and the Breakout deck that facilitates the development of new hardware designs. Although 20 documents mentioned the creation of new hardware, custom decks or added sensors, only one clearly mentioned the use of the Breakout deck. Three of the available decks have never been mentioned in any study. These are the LED-ring, equipped with several strong LEDs that can be used to create custom patterns, the Buzzer deck, a simple way to create sounds for the Crazyflie, and the BigQuad deck. The BigQuad allows using the Crazyflie 2.x as a flight controller for a larger drone.

3.9. Crazyflie State Estimation

According to the documentation provided by the producer [38], the estimation of the state of the Crazyflie can be done out of the box using two different filters: a very simple complementary filter and a more complex and comprehensive Kalman filter. The complementary filter is considered an easy-to-implement and efficient filter that is generally used with only gyroscope and accelerometer data as inputs. This estimator has been extended to also receive data from altitude sensors such as the Z-ranger. The estimated outputs are the drone's kinematic attitude (roll, pitch and yaw angles) and altitude (z). This estimator is the one defined as the default estimator in the Crazyflie firmware only if there is no deck that requires the use of the extended Kalman filter.

The extended Kalman filter (EKF), depicted in Figure 13, is a more complex estimator than the complementary filter because it accepts inputs from more internal (gyroscope, accelerometer) and external (Loco Positioning System) sensors. Only with this filter can both the vehicle's orientation and position be estimated. The Kalman filter is an algorithm that uses a sequence of measurements from several sensors to obtain state estimates, along with the system's mathematical model. In addition to the default inputs that are used to estimate the attitude, position and velocity of the Crazyflie, there are also other methods that could be employed to find the parameters of the Crazyflie. For example, the camera on AI Deck could be used to implement visual state estimation algorithms, a method showcased in works like [39]. Another example is presented in [40], where the information from the camera is used to localize another flying drone.

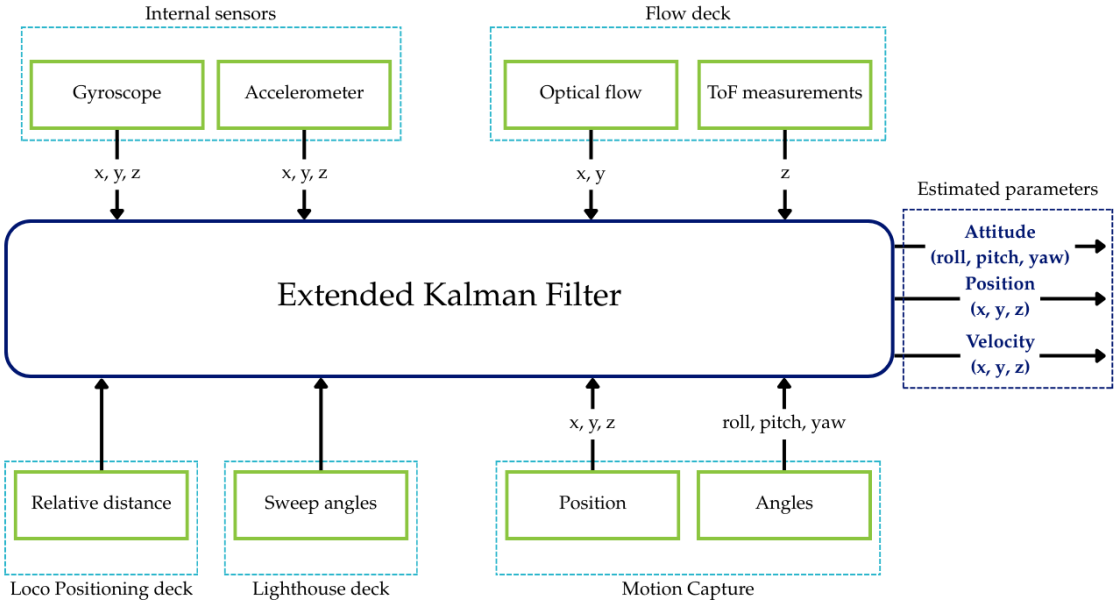


Figure 13. The extended Kalman filter used for state estimation of the Crazyflie.

3.10. Crazyflies in Simulations and the Usage of ROS

When it comes to reproducing Crazyflie behavior in simulations, there are several opportunities, as shown in the 47 documents that used different simulation approaches. An overview of the number of papers that used simulations and other software is shown in Table 7.

Within this group of tools, the physics-based simulator Gazebo [41] stands out with 23 appearances. Although the Crazyflie model and Gazebo controllers are still considered experimental, they remain among the most widely used simulation platforms. The use of Webots [42] is also worth mentioning, as it appeared in 14 papers and already has some implementations for the Crazyflie. The Webots simulator includes a Crazyflie model and some demos provided by Bitcraze. RViz [43] and Gym-Pybullet [44] appear less frequently, with 10 and seven entries, which may reflect their use in more specialized contexts such as reinforcement learning, visualization, or debugging rather than as full end-to-end simulation frameworks.

Table 7. Simulation and other software used.

Type	Number of Appearances
Gazebo	23
Webots	14
RViz	10
Gym-Pybullet	7
CrazyS	5
CrazySim	3
Sim_CF2	0
ROS/ROS 2	85
Crazyswarm	42

For software-in-the-loop (SITL) simulations there are different options available, most notably CrazyS, CrazySim and Sim_CF2. CrazyS [45] extends the ROS package RotorS to model, develop, and integrate the Crazyflie nano-quadcopter within Gazebo. CrazySim [46] is a simulation platform that executes the Crazyflie firmware in a virtual environment, while interfacing directly with Gazebo's sensor models and physics engine. The simulated firmware connects to a custom CFLib, allowing users to emulate the behavior of CFLib scripts that would normally control one or more physical Crazyflies. The Sim_CF2 simulator mainly reuses the motor model and several sensor models from RotorS; in addition, it offers support for both SITL and hardware-in-the-loop (HITL) simulation of the Crazyflie. CrazyS and CrazySim have been mentioned in only five and three papers, respectively, with Sim_CF2 having 0 appearances. This implies that, while they serve specific research communities, they have not achieved the same level of interest as real-time experiments.

ROS/ROS 2 is used in 84 studies, making it a backbone for many Crazyflie experiments. Crazyswarm [47], with 41 appearances, is another important architecture defined for controlling large swarms of Crazyflie quadcopters. Essentially, the Crazyswarm server program is a ROS node with a Python wrapper for the ROS interface. It has several drivers for different common motion capture systems and an optimized broadcast communication system that requires fewer radios per Crazyflie. Crazyswarm can also be used together with Crazysim, which relies on CFLib as a backend to provide a ROS 2 interface for drone experiments.

3.11. Research Topics

The analyzed documents have been systematically categorized into key research topics to provide a way of understanding advancements in the field. The main topics and the number of papers in which they appear are shown in Table 8. In the last column, the 15 most cited papers from that category are listed. A full list of paper titles and DOIs, together with the topics they focused on, is available as Supplementary Material, in Table S1. There may be cases where a paper fits into more than one category, which is why it appears more than once in the table.

Table 8. Crazyflie research topics.

ID	Topic	Total Number of Papers	Example of Papers
1	Control Systems and Flight Stabilization	135	[9,17,48–60]
2	Autonomous Navigation and Obstacle Avoidance	96	[10,13,15,61–72]
3	Swarms and Multi-Agent Systems	96	[51,52,54,61,63,64,73–78]
4	Monitoring, Inspection and Environmental Applications	92	[12,15,52,69,71,73–75,79–83]
5	Sensing, Localization and Sensor Fusion	69	[11,14,48,66,68,70,71,75,78,84–89]
6	Safety-Critical Applications and Security	37	[63,69,72,74,90–100]
7	Artificial Intelligence Applications	17	[9,10,58,63,66,70,71,75,85,87,101,102]
8	Simulation and Development Tools	17	[1,11,46,54,65,76,103–111]

The theme of Control Systems and Flight Stabilization encompasses fundamental techniques such as attitude and position control, including PID controllers, Kalman filters, and Model Predictive Control (MPC). These approaches are crucial for maintaining stable flight and accurate trajectory tracking, enabling Crazyflie drones to perform precise maneuvers and maintain desired flight paths under varying conditions.

Autonomous Navigation and Obstacle Avoidance focus on enabling drones to plan paths and navigate environments independently. This includes path planning, collision-avoidance strategies, and vision-based navigation systems that enable drones to perceive and respond to their surroundings without human intervention.

Swarms and Multi-Agent Systems involve the coordination of multiple drones working collaboratively. Key topics include formation control, flocking behavior, and heterogeneous systems, which enable multi-drone cooperation to solve complex tasks such as area coverage, synchronized movements, and collective decision-making.

Monitoring, Inspection, and Environmental Applications highlight the use of Crazyflie drones for practical applications such as infrastructure inspection and environmental monitoring. These application-driven tasks leverage the drone's capabilities to collect data, assess conditions, and conduct inspections in areas that are difficult or hazardous for humans to access.

Sensing, Localization, and Sensor Fusion cover the integration of various sensory inputs to improve the drone's perception capabilities or map the environment. Techniques

such as simultaneous localization and mapping (SLAM), localization (e.g., ultra-wideband), and the introduction of new sensors are sub-themes addressed by papers in this category.

Safety-Critical Applications and Security address the robustness and protection of drone systems. This includes safety filters, fault-tolerance mechanisms, and security protocols designed to defend against cyberattacks, ensure reliable operation, and safeguard communication channels through encryption.

Artificial Intelligence Applications explores the application of advanced AI techniques, including neural networks, reinforcement learning, and convolutional neural networks (CNNs). These methods enhance control algorithms and perception capabilities, enabling drones to learn from data, adapt to new scenarios and improve performance.

Several datasets related to the Crazyflie drone have resulted from research on the topic of Artificial Intelligence. For instance, refs. [10,15] present a series of images taken with a custom camera deck and are utilized to train lightweight CNNs for visual navigation. In [112] a series of battery voltages and Crazyflie positions is made available. This data is used to approximate the way the battery discharges based on a planned trajectory. The CrazyPAD dataset [92] provides comprehensive telemetry data used specifically for training Machine Learning (ML) classifiers to detect structural faults and propeller degradation in real time. Aerodynamic force data collected in air ducts [113] is used to train neural network-based flight controllers capable of stabilizing the drone in turbulent environments. Data used to train an adaptive foundation policy is available in [114], enabling the drone to generalize flight behaviors across varying dynamic environments. Finally, comprehensive attitude and position datasets from [115] have proven instrumental in training Spiking Neural Networks that leverage highly energy-efficient, low-latency control architectures ideally suited for the Crazyflie's limited power.

Simulation and Development Tools are software frameworks, platforms, and simulators that support drone development and testing. Papers that present tools such as Crazyswarm or CrazySim fit this category.

Many papers could not be classified into a single field, as they address a range of topics. Table 9 emphasizes how certain research topics naturally co-occur, revealing combinations of methods and application goals in Crazyflie studies. Only groups that have a total number of appearances greater than 20 are present. Table 9 also highlights papers that had their research focused on both of those two domains.

Table 9. Topics that appeared together the most.

IDs of Topics	Number of Appearances	Example of Papers
1 & 7	35	[9,58,102,116–122]
2 & 3	32	[61,64,72,79,123–131]
2 & 7	31	[10,15,66,97,130,132–137]
3 & 7	23	[130,138–147]
2 & 5	23	[62,66,68,70,71,148–154]
5 & 7	22	[39,40,70,85,87,148,152,155–158]

The most prominent pairing is between Control Systems and Flight Stabilization (ID 1) and Artificial Intelligence Applications (ID 7), which appears in 35 papers. Papers used learning-based techniques to improve low-level control performance and robustness, for example, through model-based reinforcement learning for applications such as learning to fly [58] or land [102,119], or deep learning for pose estimation [117]. Within this group, several highly cited works demonstrate how neural networks and reinforcement learning can be embedded directly into the control loop of a nano-quadrotor [120,122], confirming that advanced AI methods are moving from theory into experimentally validated flight controllers on Crazyflie platforms.

Another frequently observed combination links Autonomous Navigation and Obstacle Avoidance (ID 2) with Swarms and Multi-Agent Systems (ID 3), appearing in 32 papers. This pairing illustrates how navigation problems are increasingly framed at the fleet level, where collision avoidance, trajectory planning and task allocation must be solved for multiple cooperating drones operating in cluttered environments. Representative works in this category address temporal-logic-constrained multi-drone missions [61], decentralized swarm navigation in environments with obstacles [123,125], and cooperative target tracking, all implemented and validated with Crazyflie hardware.

The intersection between Autonomous Navigation and Obstacle Avoidance (ID 2) and Sensing, Localization and Sensor Fusion (ID 5), which appears in 23 papers, underlines the crucial role of perception in enabling reliable navigation [66,68]. Studies in this joint category typically combine UWB [149], optical flow [66], depth sensing, or motion capture with filtering to obtain accurate state estimates that feed higher-level planners. Many of these works exploit Crazyflie's modular decks together with sensor fusion algorithms and, in some cases, learning-based methods [71], to achieve robust indoor navigation and trajectory tracking in the presence of noise and occlusions [70]. Robust dead reckoning is critical to bridging the gap between low-frequency SLAM and GPS-denied or restricted environments. By also fusing data from the onboard IMU and AI Deck camera, the work in [159] feeds the estimator with more information, improving localization accuracy. SLAM is another field that has received significant attention in Crazyflie research in works such as [154,160], where authors leverage the full capabilities of the Crazyflie development environment to develop new mapping and localization algorithms. To achieve SLAM, researchers typically equip the Crazyflie with the Multi-ranger deck, which provides distance measurements using time-of-flight sensors in five directions (front, back, left, right and up). The problem that occurs is that the measurements are sparse. In [161], the problem was tackled using a graph-based method. Other approaches include assuming the space is a Manhattan world, as in [162]. This tight coupling of navigation and sensing themes shows that improvements in localization and perception directly translate into more capable autonomous behaviors on resource-constrained platforms.

Artificial Intelligence Applications (ID 7) appears alongside other themes, such as Swarms (ID 3) and Sensing and Localization (ID 5), highlighting how data-driven methods are increasingly integrated across nearly all aspects of Crazyflie research. The 23 papers that link Swarms (ID 3) and Artificial Intelligence (ID 7) explore topics like natural language methods for trajectory generation [142,143] or reinforcement learning for flocking [145]. Similarly, the 22 papers where Sensing, Localization and Sensor Fusion (ID 5) co-occurs with Artificial Intelligence (ID 7) employ deep neural networks for vision-based detections [39,40], depth estimation [152], or pose estimation [85].

3.12. Crazyflie Expansion Decks Used in Research Topics

Each experiment and research objective needs certain equipment. For this reason, an analysis of what expansion decks have been used in specific fields of study has been conducted and summarized in Table 10. In this table only the three most used decks per theme were included.

Positioning systems such as motion capture, Loco Positioning, or Lighthouse are not included in Table 10, but all categories are dominated by one of these systems. Marker-based motion capture systems have been the most popular across all categories, with the latter two also frequently used in experiments.

Across nearly all research topics, the Flow deck emerges as a foundational component, particularly within topic 1 (21 appearances), 2 (22) and 5 (24). This presence underscores the importance of the onboard velocity and height estimation facilities offered by the Flow

deck for stable flight and reliable state estimation. The AI deck shows a strong alignment with applications from Artificial Intelligence Applications, where it appears in 23 papers, with Autonomous Navigation and Obstacle Avoidance (19) and Sensing, Localization and Sensor Fusion (15). The integration of a camera enables experiments involving visual navigation, and, at the same time, it offers enhanced processing capabilities and faster on-board calculations that machine learning and reinforcement learning algorithms need.

Table 10. Research topic and the expansion decks used.

Theme ID	Research Topic	Deck Used	Number of Appearances Together
1	Control Systems and Flight Stabilization	Flow deck AI deck Multi-ranger	21 7 6
2	Autonomous Navigation and Obstacle Avoidance	Flow AI Multi-ranger	22 19 7
3	Swarms and Multi-Agent Systems	Flow AI Custom	10 6 5
4	Monitoring, Inspection and Environmental Applications	Custom Flow AI	7 6 4
5	Sensing, Localization and Sensor Fusion	Flow Custom AI	24 17 15
6	Safety-Critical Applications and Security	Flow Multi-ranger Micro SD Z-ranger	5 3 1 1
7	Artificial Intelligence Applications	AI Flow Custom	23 17 8
8	Simulation and Development Tools	AI Flow Breakout Micro SD	1 1 1 1

Custom expansion decks play a particularly important role in application-driven and sensing-focused subjects. Their frequent appearance in Sensing, Localization and Sensor Fusion (17) and Monitoring, Inspection and Environmental Applications (7) suggests that off-the-shelf hardware is sometimes insufficient for specialized sensing requirements. Researchers often design custom decks to integrate novel sensors or experimental hardware, highlighting both the flexibility and extended capabilities of the Crazyflie ecosystem. This also indicates that hardware innovation remains an active area, especially when unique sensing modalities or domain-specific measurements are required.

In contrast to other themes, the fields of Safety-Critical Applications and Security or Simulation and Development Tools show a more limited and less diverse use of expansion decks.

Table 10 also highlights several clear opportunities for future research by revealing underexplored combinations of research subjects and expansion decks. The Simulation and Development Tools theme exhibits almost no integration with physical expansion decks,

pointing to a gap in hardware-aware simulation, digital twins, and hardware-in-the-loop workflows that could better bridge simulation and real-world deployment.

4. Discussions and Conclusions

The evolution of research in aerial robotics and autonomous drones has created a need for open-source platforms for testing, learning, and experimenting. The evaluation of such systems is necessary to understand how and to what extent they can be used efficiently and to better understand their capabilities. The Crazyflie nano-drone has emerged as a strong candidate for nano-aerial robotics research and education, and this paper presents key advantages and abilities of this open-source platform.

The Crazyflie ecosystem has enabled access to experimental aerial robotics, fostering a continually expanding research community. This study provides valuable information for anyone who wants to start working with the Crazyflie drone or similar unmanned aerial vehicles, whether as a research project or in an educational setting. Given the research topics presented, this review can also serve as a guideline for selecting the optimal combination of hardware and software resources for the task at hand.

4.1. Study Synthesis and Limitations

This scoping review synthesized key findings from 321 papers on Crazyflie drones, published between 2015 and 2025. The analysis highlights the diversity of methodologies employed and provides significant insights into current applications and challenges in this field.

Several statistical examinations have been performed on the database, computing relevant metrics. The number of papers using Crazyflies has sharply risen in recent years, underscoring the field's significance. Studies have been published through several channels, with the largest number appearing in conference proceedings. Several institutions are at the forefront of using the Crazyflie platform in research: ETH Zurich with 20 publications, University of Bologna, Delft University of Technology, Universita della Svizzera Italiana, Tsinghua University, and the University of Toronto, all with nine publications each.

Some publications also stood out because of the total number of citations reported by the Web of Science database. The top three most cited papers that have used the Crazyflie drone, refs. [1,9,10] combine a total of 367 citations. Their prominence reflects the Crazyflie's extended capabilities and the opportunities this type of drone offers.

A limitation of this study is the inclusion of only a subset of documents from the Google Scholar database, covering the period from 14 October 2024 to 15 September 2025, as it would have been unfeasible to analyze all papers on the Crazyflie from this database. The dataset contains incomplete metadata, including missing cited references, keywords, affiliations, and publication venues in some records, which constrained the depth of citation-based and collaboration analyses. In addition to this, the manual corrections made to the metadata could be affected by human bias. Another challenge in this review is charting the thematic fields for each paper. This process could be biased because it relies on the author's personal interpretation.

4.2. The Evolution of the Crazyflie Environment

The use of Crazyflie versions in the reviewed literature demonstrates a clear evolution and diversification aligned with technological advancements and research needs. Various iterations of the Crazyflie platform have been examined, often highlighting the integration of different expansion decks to extend their functionality. This progression has enabled more complex applications, such as swarm coordination, autonomous navigation, and environmental sensing. The distribution of studies across Crazyflie versions reflects

researchers' adaptation to the platform's modularity, with Crazyflie 2.1/2.1+ currently leading in the literature, with 115 manuscripts that include these versions. At the same time, there might be a rise in applications with the newest, most performant model yet, the Crazyflie Brushless, that will pave the way for longer, more stable flights.

Across the analyzed literature, the Crazyflie platform demonstrates remarkable modularity through its expansion deck ecosystem, which enables flexible combinations of sensing, positioning, and computational upgrades. Different general-purpose positioning systems (e.g., OptiTrack) and those specifically designed for the Crazyflie ecosystem (e.g., Loco Positioning) have been used in the research papers analyzed. Motion capture and active marker decks have been overwhelmingly preferred (159 papers) compared to other positioning systems. This choice offers greater tracking precision, but it also means higher expenses due to the system's price. Alternatives designed specifically for the Crazyflie, such as the Loco Positioning System (52 papers) and Lighthouse positioning (37 papers), offer onboard localization with reduced dependence on external computation, marking progress toward fully autonomous operation, though at reduced precision (centimeter-level). Among the range of sensors used for flight stabilization, the Flow deck stands out as a standard choice for onboard velocity estimation and height control, compared to the less capable Z-ranger. With the computational expansion and the camera the AI deck provides, interest in onboard visual processing and edge computing could be satisfied. Notably, some decks (LED-ring, Buzzer, BigQuad) have seen no adoption in the literature, suggesting they either serve niche functions or lack research relevance compared to sensing and localization hardware. Although most authors chose to use commercially available decks for very specific tasks, custom hardware has also been developed, demonstrating the Crazyflie's adaptability.

In terms of simulation and software integration, Gazebo and Webots lead as the most used physics-based platforms, emphasizing the importance of realistic simulation for controller testing and algorithm validation. However, specialized SITL frameworks such as CrazyS, CrazySim, and Sim_CF2 remain underutilized, with fewer than five papers each, indicating that simulation-based Crazyflie research still needs to be developed. ROS frameworks and Crazyswarm form the software backbone of some experimental setups, enabling scalability and integration with motion capture or positioning systems. Their widespread adoption reflects a strong tendency toward standardized, open-source robotic architectures within the Crazyflie research community. The use of ROS and Python-based tools across the literature lowers the barrier for educators seeking standardized, research-aligned teaching materials.

The articles were categorized by their thematic focus, with consideration of the expansion decks used. This categorization sheds light on how hardware facilitates the broadening of research areas and the complexity of applications. It also highlights the significance of modular design in supporting diverse experimental configurations and enabling iterative enhancements, making it ideal for varied educational settings. The research shows that almost all reported applications in the state of the art operate in indoor environments. This is due to the drone's physical construction (nano category), which makes it less suitable for outdoor applications. The prevalence of papers focused on Control Systems and Flight Stabilization as the main research topics underscores the Crazyflie's suitability for testing new control algorithms. The platform is open source and has easily accessible controller parameters, making it a good candidate for rapidly prototyping and testing new control methods. The analysis of topic co-occurrences indicates a shift from basic stabilization to advanced autonomy, as evidenced by the notable overlap between Control Systems and Artificial Intelligence Applications. This suggests that the community is increasingly using

the Crazyflie to apply learning-based methods, such as reinforcement learning and neural networks, in control algorithms.

Another key insight from our evaluation is that the Crazyflie is frequently and effectively used as a standard unit for decentralized fleet coordination. The frequent appearance of these themes underscores the platform's role in addressing scalable navigation challenges, where multiple cooperating agents must perform real-time collision avoidance and trajectory planning. These findings also highlight that educators can design curricula that progressively build complexity, from low-level control to multi-agent systems, using a single platform, thereby reducing complicated setups, while maximizing learning outcomes.

The analysis of hardware utilization within these research subjects further demonstrates how the platform's modularity enhances research capabilities. The Flow deck has become the primary sensor for maintaining stability across almost all categories. Furthermore, the AI deck plays a crucial role in edge computing research, enabling the deployment of onboard deep learning models that were previously too computationally intensive for nano-UAVs like the Crazyflie. The frequent use of custom decks in monitoring and inspection applications indicates that, although the commercial ecosystem is strong, specific environmental applications often necessitate tailored sensor integration. Conversely, the limited use of physical expansion decks in simulations highlights a noticeable gap in the literature. Current simulators may not yet fully replicate the varied sensor configurations used in physical experiments, suggesting a need for more accurate digital twins in future development tools.

A limitation of the analysis of the evolution of the Crazyflie environment can be the lack of in-depth analysis and comparison for some topics presented, such as the drone's mathematical model. A more thorough examination could help uncover more about these relevant subjects.

4.3. Open Challenges

There have been tremendous advancements made since the introduction of the Crazyflie drone, with applications diversifying and hardware evolving. At the same time, based on the gaps identified in this review, future research should prioritize bridging the gap between simulation environments and physical hardware capabilities. The analysis revealed a notable scarcity of studies integrating expansion deck models into simulation tools, highlighting a critical need for high-fidelity digital twins and hardware-in-the-loop workflows that accurately reflect the platform's modular sensing and processing constraints. Furthermore, the lack of work on the kinematic models of the Crazyflie 2.1+ or Crazyflie Brushless could be an interesting research direction that would sustain the development of new complex control algorithms or simulations. Additionally, while the Crazyflie 2.1 remains the standard, the emergence of the Crazyflie Brushless, featured in only a single study to date, offers a significant opportunity to expand the experimental boundaries for flight duration and payload capacity. As AI-based control and perception continue to grow (especially reinforcement learning in drones), future studies could also address safety and interpretability deployed on Crazyflie's resource-constrained environment.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/drones10040261/s1, excluded fields of study from the database search, File S1: Full search strategy; Table S1: Abstract synonyms list; Table S2: Abstract words to remove list; Table S3: Papers with extracted data; PRISMA Checklist: Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist.

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