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Review

A Review and Bibliometric Analysis of Unmanned Aerial System (UAS) Noise Studies Between 2015 and 2024

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Abstract: Unmanned aerial systems (UAS), commonly known as drones, have gained widespread use due to their affordability and versatility across various domains, including military, commercial, and recreational sectors. Applications such as remote sensing, aerial imaging, agriculture, firefighting, search and rescue, infrastructure inspection, and public safety have extensively adopted this technology. However, environmental impacts, particularly noise, have raised concerns among the public and local communities. Unlike traditional crewed aircraft, drones typically operate in low-altitude airspace (below 400 feet or 122 m), making their noise impact more significant when they are closer to houses, people, and livestock. Numerous studies have explored methods for monitoring, assessing, and predicting the noise footprint of drones. This study employs a bibliometric analysis of relevant scholarly works in the Web of Science Core Collection, published from 2015 to 2024, following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) data collection and screening procedures. *The International Journal of Environmental Research and Public Health*, *Aerospace Science and Technology*, and the *Journal of the Acoustical Society of America* are the top three preferred outlets for publications in this area. This review unveils trends, topics, key authors and institutions, and national contributions in the field through co-authorship analysis, co-citation analysis, and other statistical methods. By addressing the identified challenges, leveraging emerging technologies, and fostering collaborations, the field can move towards more effective noise abatement strategies, ultimately contributing to the broader acceptance and sustainable integration of UASs into various aspects of society.

Keywords: unmanned aerial systems (UASs); noise assessment; bibliometric analysis; literature review

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1. Introduction

Aircraft-induced noise has garnered significant attention due to its negative impact on local communities. The considerable noise disturbance from manned aircraft during traffic patterns adversely affects nearby residents' mental and physical well-being, which includes health impairment, annoyance, and learning disorders [1,2]. This environmental effect often leads to annoyance and complaints about airport operations, management, planning, and expansion [3,4]. The U.S. Federal Aviation Administration (FAA) regulates airports to develop noise abatement and mitigation plans to comply with compatible land planning [5,6]. The International Civil Aviation Organization (ICAO) identifies mitigating and reducing aircraft noise as top initiatives, following up on possible environmental issues from the operation of Emerging Technology Aircraft (ETA), including urban air mobility concepts, unmanned aircraft, and remotely piloted aircraft [7,8]. However, the current FAA's noise certification standards that apply to individual UASs were still under development due to the unavailability of applicable noise certification standards when aircraft were presented for certification [9].

Unmanned aerial systems (UASs), commonly known as drones, have gained widespread use across various sectors due to their flexibility and affordability. Fields such as aerial imaging, agriculture, firefighting, search and rescue, infrastructure inspection, wildlife monitoring, and public safety have widely adopted various UAS platforms. With the rise of consumer-level UASs in recent decades, including propeller and fixed-wing UASs, there has been a notable change in fleet sizes and operational altitudes. UAS platforms are much smaller than manned aircraft and typically operate in low-altitude airspace (below 400 ft), bringing them closer to ground-level individuals [10–13]. This proximity highlights the need for innovative noise monitoring and assessment methodologies to better understand the aeroacoustic and psychoacoustic impact of UAS noise on local communities. On the other hand, effective and accurate acoustic monitoring is crucial for drone detection and classification, emphasizing the importance of active drone noise monitoring, assessment, and prediction [14,15]. Therefore, as UAS noise has been identified as a critical concern for public acceptance [15,16], it is essential for stakeholders to monitor and assess UAS noise effects to ensure effective noise abatement and control.

Acoustic engineering is the primary field used to monitor UAS noise. Most UAS noise monitoring and assessment approaches can be traced back several decades to when propeller- and fixed-wing-induced noise was extensively investigated [17,18]. There are significant differences between UAS noise and traditional manned aircraft noise, including the design of the propeller [19–22], operational modes [23,24], and traffic patterns [11,12,16,25–27].

However, there is a lack of an in-depth understanding of synergetic studies on UAS noise monitoring, assessment, and predictions. Therefore, three research questions are developed as follows:

1. What is the current state of scientific studies on UAS noise monitoring, assessment, and predictions?
2. What are the trends regarding topics, active researchers, and collaborations of these studies?
3. What are the challenges and future opportunities of scientific studies on UAS noise monitoring, assessment, and predictions?

This review aims to contribute to the existing body of knowledge by addressing the aforementioned research questions. Methodologically, bibliometric analysis and bibliographic coupling were employed to summarize the current state of relevant studies, identify co-authorship and co-citation patterns, unveil collaboration links across institutions and nations, and analyze emerging trends and topics [28]. A systematic literature review focused on a curated selection of literature refined through specific inclusion and exclusion criteria. Key methods, topics, limitations, and challenges within the reviewed studies were synthesized to highlight opportunities and future directions [29]. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, which was designed to help systematic reviewers transparently report the purpose, procedures, and findings of their reviews, was utilized as a standardized protocol to ensure a rigorous and scientific approach to conducting systematic literature reviews [30,31].

Therefore, this study applied bibliometric analysis, bibliographic coupling, and citation analysis, following the PRISMA method, to systematically examine scientific literature on UAS noise monitoring from 2015 to 2024 [32]. Co-citation analysis and collaboration mapping revealed this field's current state and trends. VOSviewer was used for data visualization [33]. Additionally, this study illuminates the challenges and future opportunities in UAS noise monitoring.

This study is organized as follows: Section 2 details the materials and methods used, and Section 3 presents the results. Section 4 discusses the limitations and potential directions for future UAS noise prediction studies. Finally, Section 5 concludes the review with several critical remarks.

2. Materials and Methods

PRISMA guidelines only apply to data collection and screening procedures in this review. This project was registered in the Open Science Framework (OSF) with the identifier DOI 10.17605/OSF.IO/MKN7R and is fully open access.

2.1. Identify Keywords and Initial Search

This review uses the Boolean search method on a set of keywords, and set of "UAS", "Drone", "Uncrewed Aerial Vehicles", and "Unmanned Aerial Vehicles", and "Noise" and "Monitoring", "Evaluation", "Assessment", and "Prediction". is considered. Therefore, the search syntax for the full-content search from the Web of Science Core Collection is "(ALL = (UAS) OR ALL = (Drone) OR ALL = (Uncrewed Aerial Vehicles) OR ALL = (Unmanned Aerial Vehicles)) AND ALL = (Noise) AND (ALL = (Monitoring) OR ALL = (Evaluation) OR ALL = (Assessment) OR ALL = (Prediction))".

2.2. Configure Exclusion and Inclusion Criteria

This review establishes essential exclusion and inclusion criteria throughout multiple rounds of the screening process. First, the timestamps of selected studies were limited to those published between 1 January 2015 and 1 January 2024. Additionally, only English-written, peer-reviewed journal articles were included. From the first round to the third round, the authors selected studies relevant to drone noise monitoring, evaluation, assessment, and prediction, considering different levels of completeness. In the first round, the authors examined only the titles. In the second round, they reviewed the abstracts. The final round of screening involved a full-text review.

2.3. Preliminary Most Local Cited References Examination

One innovative strategy employed by the authors in this study was the preliminary examination of the most locally cited (LC) references from the final screening results. This strategy aimed to complement relevant studies missing in the original search. This process identifies highly cited studies from 2015 to 2024. After thoroughly reviewing these studies with the same exclusion and inclusion criteria, eligible articles were added to the final dataset.

2.4. Assessment of Full Bibliometric Information for Eligibility

The final step was to review the full paper from the combined, filtered datasets from 2.2. and add a dataset from 2.3. The eligibility of studies was assessed based on the relevance of UAS noise monitoring, assessment, and prediction. The eligible literature was included in this study's final bibliometric and citation analysis dataset.

2.5. Limitations

One limitation of this review is the exclusion of conference proceedings, book chapters, and other resources outside the Web of Science Core Collection database. Given the lengthy review, revision, and resubmission process typical of peer-reviewed journals, these sources might contain more current information. Future studies might consider incorporating additional databases, such as Scopus and ProQuest, to enhance the breadth and diversity of the reviewed literature.

Another limitation is the scope of this review regarding the distinction between UAS, Vertical Takeoff and Landing (VTOL), and electric Vertical Takeoff and Landing (eVTOL) aircraft. While VTOL and eVTOL are emerging components of urban air mobility (UAM), their noise generation and propagation mechanisms, often involving propeller-driven systems, are complex [9]. For future studies, a more refined and expanded review addressing the impact of UAM noise on low-altitude airspace is recommended.

The table in Section 3 shows that studies on UAS noise often parallel those on traditional propeller and fixed-wing aircraft noise. This suggests that future systematic literature reviews should refine and include these relevant studies for a more comprehensive analysis.

One limitation of the bibliometric analysis software is that there is a lack of flexibility in modifying the features of the labels, such as the capital letters of country and university names in visualization charts.

3. Results

The authors conducted a literature search following previously described procedures, adhering to the PRISMA methodology. Figure 1 elaborates on the overall procedure and the number of studies obtained in each round of screening.

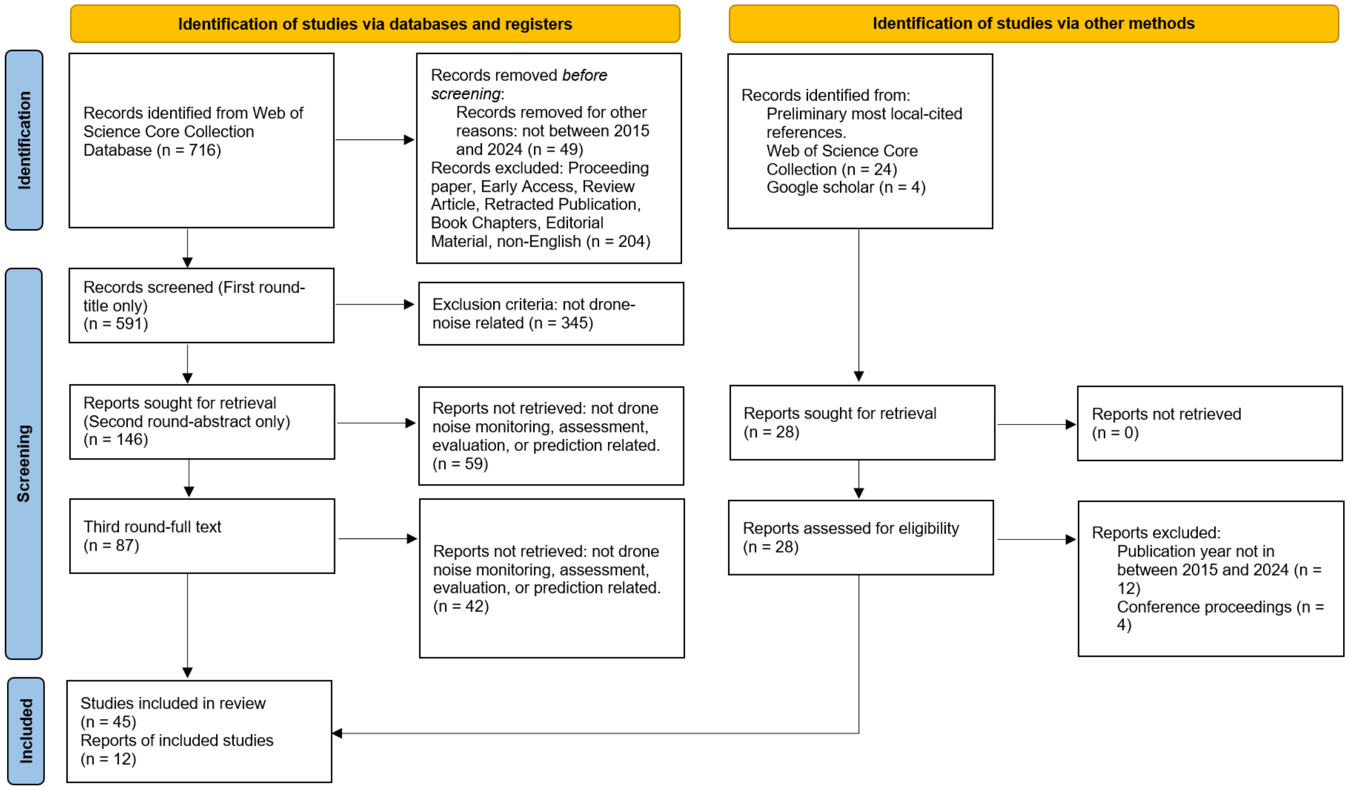

Figure 1. PRISMA flow diagram, adapted from [30].

The initial search in the Web of Science Core Collection yielded 591 articles after applying keywords and time period filters. The first round of screening, based on titles and using the established exclusion and inclusion criteria, reduced this number to 146 articles. The second round, involving a careful review of the abstracts, further narrowed the selection to 87 articles. The third round consisted of a full-text screening, resulting in 45 articles, with an additional twelve relevant articles from the preliminary examination of the most locally cited references. Consequently, the final dataset includes 57 English-written, peer-reviewed journal articles indexed in the Web of Science Core Collection Database between 2015 and 2024.

Table 1 presents the top 10 most local-cited (LC) references after adding 12 relevant studies to the final dataset for review. Five articles are excluded at the screening stage due to the time period (Williams and Hawkings, 1969; Brentner and Farassat, 2003; and Sinibaldi and Marino, 2013) and conference proceedings (Intaratep et al., 2016; Christian and Cabell, 2017).

Table 1. Most local-cited (LC) references on UAS noise monitoring, assessment, and prediction.

Title	Author, Year	Journal	Total LCS
Sound generation by turbulence and surfaces in arbitrary motion	Williams and Hawkings, 1969 [17]	*Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences*	18
Multirotor drone noise at static thrust	Tinney and Sirohi, 2018 [23]	*AIAA Journal*	16
Experimental analysis on the noise of propellers for small UAV	Sinibaldi and Marino, 2013 [34]	*Applied Acoustics*	15
Sound quality factors influencing annoyance from hovering UAV	Gwak et al., 2020 [35]	*Journal of Sound and Vibration*	11
Effects of flow recirculation on Unmanned Aircraft System (UAS) acoustic measurements in closed anechoic chambers	Stephenson et al., 2019 [36]	*The Journal of the Acoustical Society of America*	11
Acoustic signature measurement of small multi-rotor Unmanned Aircraft Systems	Kloet et al., 2017 [37]	*International Journal of Micro Air Vehicles*	10
Modeling aerodynamically generated sound of helicopter rotors	Brentner and Farassat, 2003 [18]	*Progress in Aerospace Sciences*	9
Psychoacoustic modelling of rotor noise	Torija et al., 2022 [38]	*The Journal of the Acoustical Society of America*	9
Experimental study of quadcopter acoustics and performance at static thrust conditions	Intaratep et al., 2016 [39]	*22nd AIAA/CEAS Aeroacoustics Conference*	9
Effects of a hovering Unmanned Aerial Vehicle on urban soundscapes perception	Torija et al., 2020 [10]	*Transportation Research Part D: Transport and Environment*	8
Initial investigation into the psychoacoustic properties of small Unmanned Aerial System noise	Christian and Cabell, 2017 [40]	*23rd AIAA/CEAS Aeroacoustics Conference*	8

3.1. Bibliometric and Citation Analysis

This review first examined several standard statistics, including the most relevant authors, sources, and institutions involved in UAS noise monitoring, assessment, and prediction studies (Tables 2–4). Antonio J. Torija stands out, with six pertinent research articles over the past ten years, and holds the highest number of fractionalized articles at 1.92. *The International Journal of Environmental Research and Public Health*, *Aerospace Science and Technology*, and the *Journal of the Acoustical Society of America* are the top three most productive journals, with seven, six, and five relevant publications.

Local citations (LCS) are good indicators of the overall quality, relevance, trends, credibility, and impact within a community. *The Journal of the Acoustical Society of America*, the *Journal of Sound and Vibration*, and the *AIAA Journal* are the top three journals, with 134, 107 and 94 LCS, respectively.

Table 4 presents the most significant affiliations in UAS noise problem studies. The Hong Kong University of Science and Technology (HKUST, China), the University of Auckland (New Zealand), and the University of Salford (United Kingdom) are the top three institutions with the highest research output, featuring 24, 15 and 14 relevant articles, respectively. Notably, HKUST Shenzhen Research Institute (China) and Shenzhen Research Institute (China) have six and four relevant publications, respectively. This suggests possible collaborations with HKUST, which are explored further in Section 3.1.4.

Table 2. Most relevant authors on UAS noise monitoring, assessment, and prediction.

Authors	Articles	Articles Fractionalized (Rank)
Antonio J. Torija	6	1.92 (1)
Xin Zhang	6	1.13 (2)
Siyang Zhong	5	1.02 (4)
Michael J. Kingan	5	1.04 (3)
Hanbo Jiang	4	0.84 (7)
Damiano Casalino	3	0.62 (14)
Tyaek Go Sung	3	0.83 (8)
Nathan Green	3	0.67 (9)
Riul Jung	3	0.53
Soogab Lee	3	0.92 (6)

Table 3. Most relevant sources on UAS noise monitoring, assessment, and prediction.

Sources	Articles	LCS (Rank)
International Journal of Environmental Research and Public Health	7	42 (6)
Aerospace Science and Technology	6	49 (5)
Journal of the Acoustical Society of America	5	134 (1)
Physics of Fluids	5	28 (8)
Applied Acoustics	4	60 (4)
Journal of Sound and Vibration	4	107 (2)
AIAA Journal	3	94 (3)
Drones	3	4 (69)
International Journal of Aeronautical and Space Sciences	2	3 (97)
Transportation Research Part D: Transport and Environment	2	23 (10)

Table 4. Most relevant affiliations on UAS noise monitoring, assessment, and prediction.

Affiliation (Region)	Articles
Hong Kong University of Science and Technology (China)	24
The University of Auckland (New Zealand)	15
University of Salford (United Kingdom)	14
Seoul National University (South Korea)	9
HKUST-Shenzhen Research Institute (China)	6
Korea Advanced Institute of Science and Technology (South Korea)	5
Dassault Systemes Deutschland GmbH (Germany), Shenzhen Research Institute (China)	4
RMIT University (Australia), University of Southampton (UK), University of Texas Austin (USA), University of Zagreb (Croatia), U.S. Air Force Academy (USA), Zhejiang University of Science and Technology (China)	3

Table 5 presents the studies receiving the highest global citations, using the Global Citations per Year (GCS per year) indicator to account for publication duration bias. Christiansen et al. [41] conducted the most globally cited study, "Noise Levels of Multi-Rotor Unmanned Aerial Vehicles with Implications for Potential Underwater Impacts on Marine Mammals", with a total of 107 citations. In addition, the studies by Lee, Hakjin and Lee; Duck-Joo [42]; and Casalino et al. [43] demonstrate the highest average annual citations, each achieving 12 citations per year.

Table 5. Most global-cited (GC) articles on UAS noise assessment.

Title	Author, Year	Journal	Total GCS	Mean GCS per Year
Noise levels of multi-rotor Unmanned Aerial Vehicles with implications for potential underwater impacts on marine mammals	Christiansen et al., 2016 [41]	*Frontiers in Marine Science*	107	11.89
Multirotor drone noise at static thrust	Tinney and Sirohi, 2018 [23]	*AIAA Journal*	79	11.29
Rotor interactional effects on aerodynamic and noise characteristics of a small multirotor unmanned aerial vehicle	Lee, Hakjin and Lee, Duck-Joo, 2020 [42]	*Physics of Fluids*	60	12.00
Acoustic signature measurement of small multi-rotor unmanned aircraft systems	Kloet et al., 2017 [37]	*International Journal of Micro Air Vehicles*	51	6.38
Definition of a benchmark for low Reynolds number propeller aeroacoustics	Casalino et al., 2021 [43]	*Aerospace Science and Technology*	48	12.00
Effects of a hovering Unmanned Aerial Vehicle on urban soundscapes perception	Torija et al., 2020 [10]	*Transportation Research Part D: Transport and Environment*	47	9.40
Drone noise emission characteristics and noise effects on humans—A systematic review	Schäffer et al., 2021 [44]	*International Journal of Environmental Research and Public Health*	43	10.75
Assessing the disturbance potential of small Unoccupied Aircraft Systems (UAS) on gray seals (Halichoerus grypus) at breeding colonies in Nova Scotia, Canada	Arona et al., 2018 [45]	*PeerJ*	36	5.14
Sound quality factors influencing annoyance from hovering UAV	Gwak et al., 2020 [35]	*Journal of Sound and Vibration*	35	7.0
A psychoacoustic approach to building knowledge about human response to noise of Unmanned Aerial Vehicles	Torija and Clark, 2021 [46]	*International Journal of Environmental Research and Public Health*	31	7.75

Table 6 presents studies with the highest local citations (LCS), highlighting the value and recognition these studies have received from local peers. The most locally cited article is by Tinney and Sirohi [23], with a local citation (LC) to global citation (GC) ratio of 20.25%. This LC/GC ratio is an effective indicator of how well a study aligns with the main trends within a targeted group in specific domains. Although Christiansen et al. [41] holds the highest number of global citations, its relatively low LC/GC ratio indicates that it is more frequently cited by subjects outside the UAS noise domain.

Table 6. Most local-cited (LC) articles on UAS noise assessment.

Title	Author, Year	Journal	Total LCS	LC/GC (%)
Multirotor drone noise at static thrust	Tinney and Sirohi, 2018 [23]	*AIAA Journal*	16	20.25
Effects of flow recirculation on Unmanned Aircraft System (UAS) acoustic measurements in closed anechoic chambers	Stephenson et al., 2019 [36]	*The Journal of the Acoustical Society of America*	11	36.67
Acoustic signature measurement of small multi-rotor Unmanned Aircraft Systems	Kloet et al., 2017 [37]	*International Journal of Micro Air Vehicles*	10	19.61
Psychoacoustic analysis of contra-rotating propeller noise for Unmanned Aerial Vehicles	Torija et al., 2021 [47]	*The Journal of the Acoustical Society of America*	9	30.00
Rotor interactional effects on aerodynamic and noise characteristics of a small multirotor Unmanned Aerial Vehicle	Lee, Hakjin and Lee, Duck-Joo, 2020 [42]	*Physics of Fluids*	7	11.67
Lattice-Boltzmann calculations of rotor aeroacoustics in transitional boundary layer regime	Casalino et al., 2022 [48]	*Aerospace Science and Technology*	5	10.42
Experimental and analytical investigation of contra-rotating multi-rotor UAV propeller noise	McKay et al., 2021 [49]	*The Journal of the Applied Acoustics*	5	20.00
Noise prediction of multi-rotor UAV by RPM fluctuation correction method	Han et al., 2020 [50]	*Journal of Mechanical Science and Technology*	3	25.00
Psychoacoustic modelling of rotor noise	Torija et al., 2022 [38]	*The Journal of the Acoustical Society of America*	3	30.00
Noise levels of multi-rotor Unmanned Aerial Vehicles with implications for potential underwater impacts on marine mammals	Christiansen et al., 2016 [41]	*Frontiers in Marine Science*	2	1.87

3.1.1. Co-Occurrence Analysis (Title and Abstract)

To conduct the co-occurrence network analysis at the Title and Abstract level, the minimum number of keyword occurrences was set to 5, considering the limited studies in UAS noise monitoring, assessment, and prediction. For each of the 34 keywords, the total strength of co-occurrence links with other keywords was calculated. Keywords with the highest total link strength were selected. Figure A1 in Appendix A presents two clusters: Cluster 1 includes topics such as 'measurement', 'sound pressure level', 'simulation', 'thrust', 'tonal noise', 'aerodynamic', and 'propeller'. Cluster 2 comprises 'impact', 'drone', 'operation', 'assessment', 'framework', and 'annoyance'. These clusters indicate that the relevant noise problem studies can be categorized into aeroacoustics and psychoacoustics.

3.1.2. Co-Authorship and Author Citation Analysis

Figure 2 presents a density visualization of co-authorship using fractional counting. The minimum number of documents per author was set to 3, and the weight of the links was fractionalized based on the number of co-authors of each study. Some nodes in this network are not connected to each other. Five clusters are identified in Figure 2 based on the predefined threshold. For example, two groups led by Zhang, X. and Torija, A. are disconnected, indicating no direct collaboration or relevance between their studies.

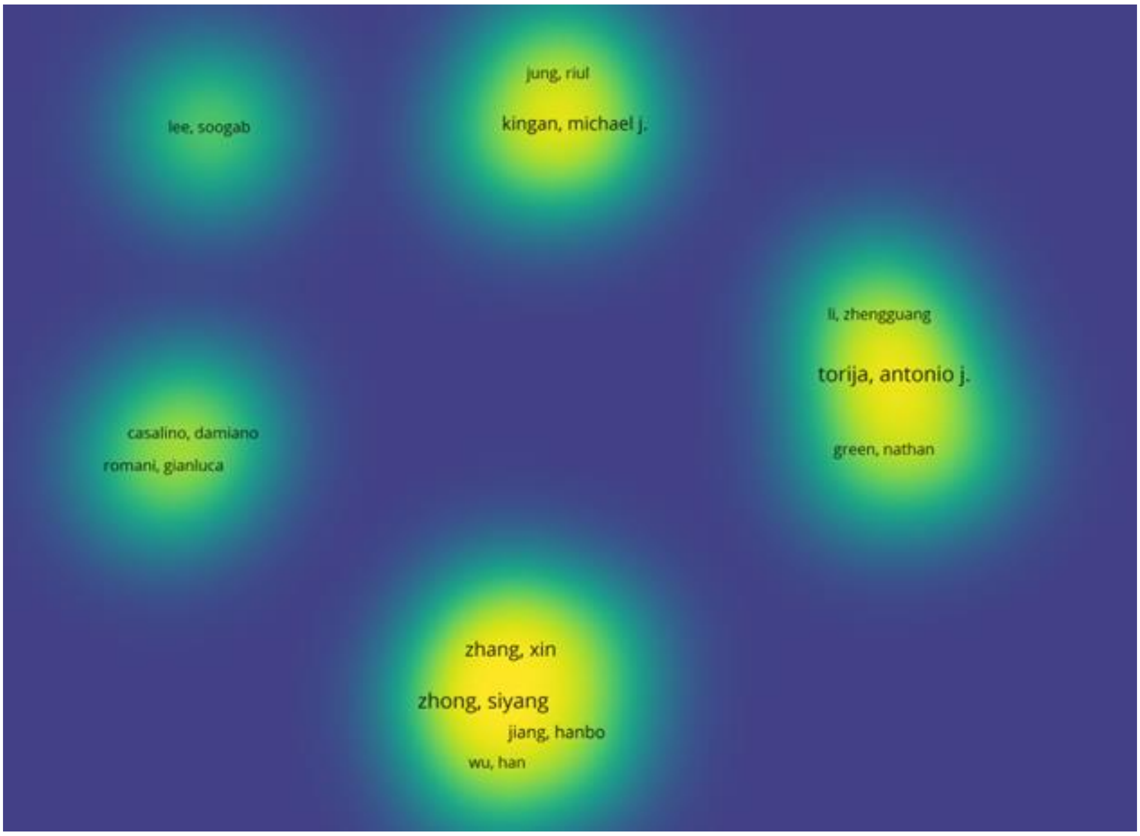

Figure 2. Density visualization of co-authorship (fractional counting).

3.1.3. Co-Citation Analysis (Literature)

A co-citation relationship is established if two or more papers are cited concurrently by one or more subsequent articles. A network visualization of co-citation is presented in Figure A2. This indicator presents the strength of the interconnection among the literature referred to in a primary article [51]. The minimum number of citations of a cited reference was set as five. In addition, Table 1, with the most local-cited references, has good agreement with the co-citation analysis.

"Multirotor Drone Noise at Static Thrust", with 16 local citations, gained the most local citations during the past decade. "Sound generation by turbulence and surfaces in arbitrary motion", with 18 local citations, gained the second most local citations and was included in the reviewed dataset.

3.1.4. Collaboration Analysis (Country and Institution)

Figure 3 presents six clusters of countries. The first cluster comprises China, the United Kingdom, and Spain. The second cluster includes the United States, South Korea, Kazakhstan, Canada, Denmark, Australia, and the United Arab Emirates. The third cluster consists of Germany, Italy, Switzerland, and Belgium. Notably, Clusters 2 and 3 are the only groups that show collaboration between groups of countries. Similarly, Figure 4 presents a collaboration network by institutions. The largest cluster is centered on the Hong Kong University of Science and Technology (China), consistent with Table 4.

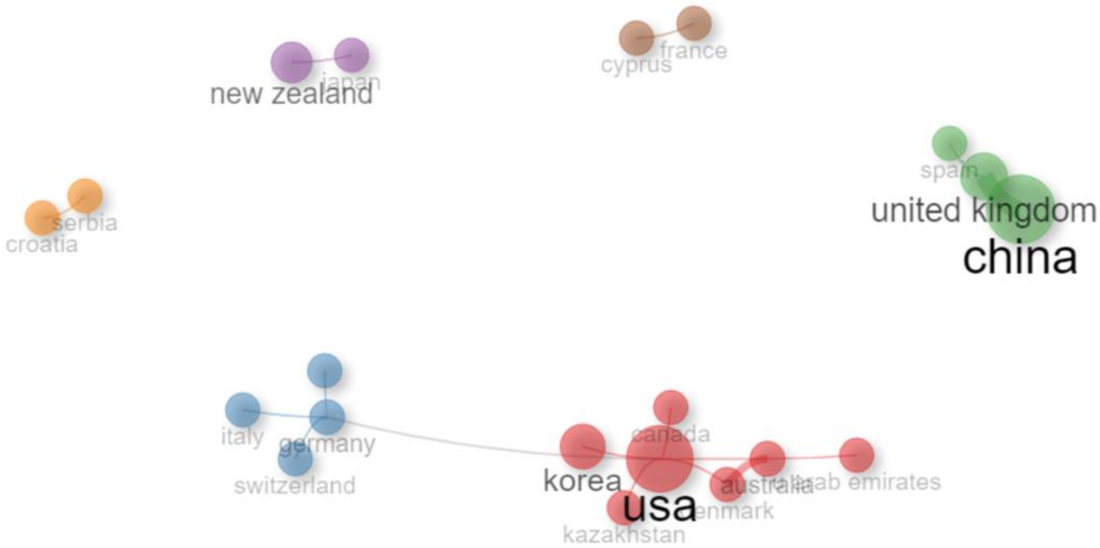

Figure 3. Collaboration network by countries.

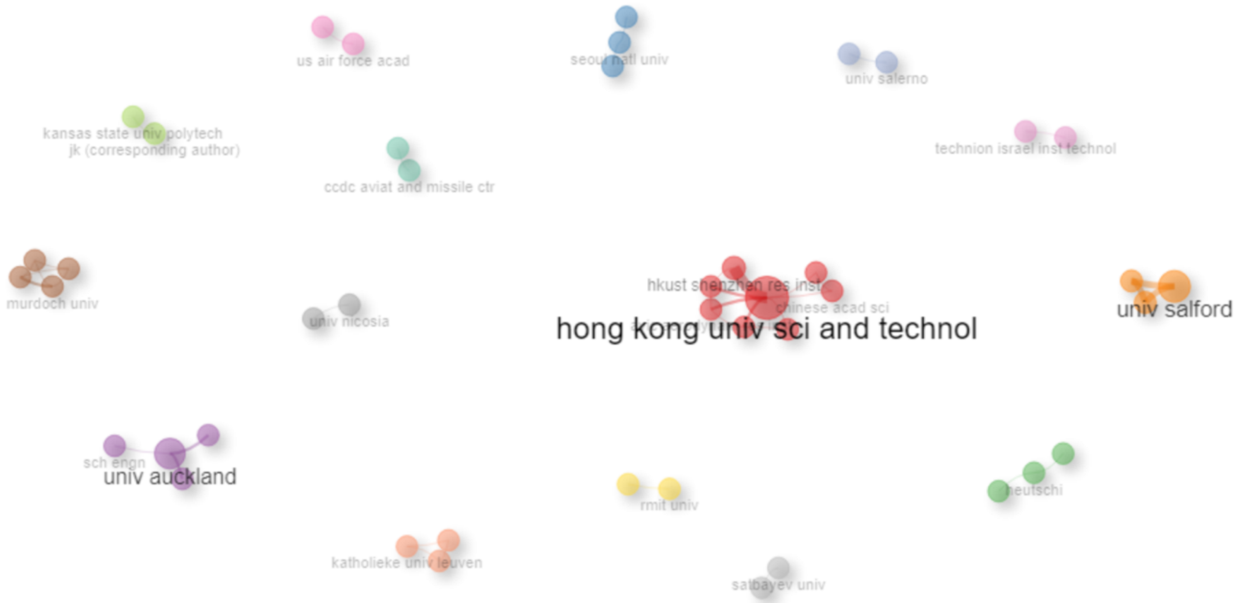

Figure 4. Collaboration network by institutions.

3.2. The Recent Progress of UAS Noise Monitoring, Assessment, and Prediction

The UAS noise problem framework, presented in Figure 5, was formalized based on our bibliometric analysis and literature review. The UAS noise problem studies, focusing on noise monitoring, assessment, and prediction, are categorized as *aeroacoustics* and *psychoacoustics*. Table 5 presents a detailed review of the literature from a macroscopic perspective. In addition, the completed list of final screened datasets is presented with identified features such as region, problem-solving and innovation, and methods (see Table 7).

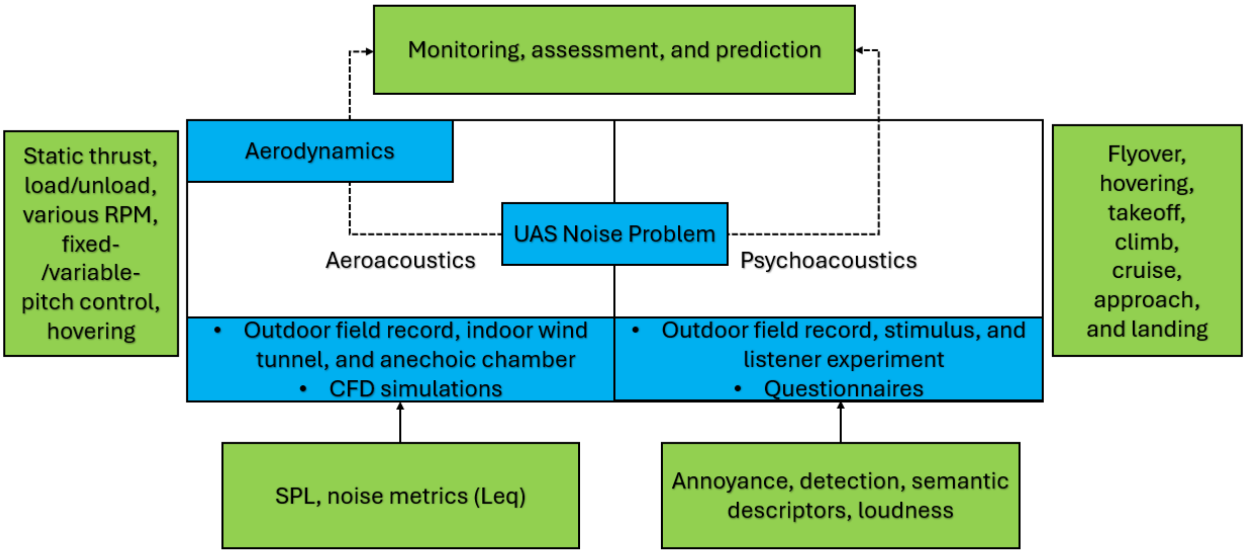

Figure 5. UAS noise problem framework.

Table 7. Review of the literature from a macroscopic perspective.

Literature (Ref.)	Region				Problem Solving and Innovation	Method
	CN	EU	Others	US		
Casalino et al., 2022 [48]		×		×	A recently developed variant of PowerFlow VLES model is validated to predict trailing edge noise radiation.	Simulation
Casalino et al., 2021 [43]		×			A preliminary step towards defining a benchmark configuration for low Reynolds number propeller aeroacoustics.	Force and noise measurements carried out in a low-speed semi-anechoic wind tunnel were compared to scale-resolved CFD simulations.
Wunderli et al., 2022 [52]		×			A modeling approach in combination with a measurement concept is validated using three different multi-copter models.	A multiple regression approach.
Jiang et al., 2022 [53]	×				Numerical simulations, including RANS and DDES computations, were conducted to evaluate the designed high-efficiency, low-noise propellers' aerodynamic and acoustic performance.	Both field experiments and simulation
Ramos-Romero et al., 2023 [54]		×			A measurement and analysis framework for the acoustic characterization of sUAS through calculating conventional noise metrics, frequency, and directivity features.	Field experiment based on a multi-channel approach, and back-propagating the sound from ground microphone to source.
Casalino et al., 2023 [20]		×			The effects of flow confinement on the noise generated by a sUAS rotor were measured and simulated in a partially closed test room.	Both field experiments and simulations were conducted.
Fruncillo et al., 2022 [55]		×			The experimental–numerical comparisons on the simulation model combine flight dynamics and aeroacoustics.	Experimental flight data were used to validate the simulation model.
Wu et al., 2022 [56]			×		A detailed investigation of tonal noise produced by a UAS rotor operating with a circular strut mounted downstream.	Experiment measurement and CFD simulations
Yu et al., 2023 [24]			×	×	Aeroacoustics attributes of fixed- and variable-pitch control drones were compared.	Simulation-based on the multirotor noise assessment framework

Table 7. *Cont.*

Literature (Ref.)	Region				Problem Solving and Innovation	Method
	CN	EU	Others	US		
Torija et al., 2022 [38]	×	×			A psychoacoustic annoyance model optimized for rotor noise to account for the perceptual effect of impulsiveness.	A listening experiment was conducted in which participants assessed a series of sound stimuli with various design parameters.
Stalnov et al., 2022 [25]			×		A framework for estimating rotor-based UAV auditory detection probability on the ground for a listener in a real-life scenario.	Outdoor soundscape recordings and measurement of propeller acoustic signature in anechoic chamber.
Jiang et al., 2021 [57]	×				The thickness noise and loading noise model of rotors has been formulated in spherical coordinates, simplifying the numerical evaluation of the integral noise source.	CFD and experiment show that the noise prediction model's performance is reliable.
Utebayeva et al., 2023 [58]			×	×	Machine learning models (SimpleRNN, LSTM, BiLSTM, and GRU) recurrent network models for real-time UAS sound recognition systems based on Mel-spectrogram using Kapre layers	Training data are collected from field experiments. Models are tested in simulation.
Ahuja et al., 2022 [59]				×	Integrate established acoustic prediction techniques directly into a surface–vorticity solver.	Embed metrics into a simple and user-friendly simulation-based flow solver.
Zhou et al., 2022 [60]	×				Noise source features of multi-rotor systems are experimentally studied using microphone arrays and the conventional beamforming algorithm.	Dual-propeller measurement and flight test in anechoic chamber.
Dbouk and Drikakis, 2021 [61]			×		A high-resolution computation methodology for predicting *aeroacoustic* footprints emitted from a swarm of multi-rotor drones.	A virtual blade model is integrated into the CFD solver to impose the propeller's downwash and upwash effects.
Bu et al., 2021 [62]	×				The influence of the propeller separation distance for various propellers at different rotation speeds and rotational directions was studied.	Field experiments in an anechoic chamber and numerical simulations.
Guo et al., 2020 [15]			×		A monitoring system that identifies and tracks illegal UAS based on acoustic features using a microphone array, a hidden Markov model (HMM), and adaptive beamforming.	Field experiments scan the sky, find sound sources, and identify illegal drones. Performance is evaluated through simulations.
Bbouk & Drikakis, 2022 [63]	×		×		A CFD study of quadcopter *aeroacoustics*, which is integrated in the framework of Reynolds–Averaged Navier–Strokes with the Ffowcs Williams–Hawkings (FW-H) model.	Simulation results agree with experimental data at a moderate computational cost.
Go et al., 2023 [64]			×		The effect of an acoustically rigid shroud on the tonal noise produced by a UAS propeller is studied.	CFD simulations showed good agreement with measurements of the time-average rotating pressure field made by a probe microphone on the inner surface of the shroud.
Gwak et al., 2020 [35]			×		*Psychoacoustic* aspects of the noise of multi-rotor UAS are studied.	The first experiment collected field UAS noise data and generated new stimuli; the second was a *psychoacoustic* experiment.
Ghoreyshi et al., 2023 [19]				×	Two different computational setups are used to study the performance and *aeroacoustics* of twelve different UAS propeller designs.	Two experiments were conducted in the wind tunnel with microphones (one fixed-position and another radially traversing).

Table 7. *Cont.*

Literature (Ref.)	Region				Problem Solving and Innovation	Method
	CN	EU	Others	US		
Alkmim et al., 2022 [65]		×			An experimental setup for measuring the sound radiation of a quadrotor UAS using a hemispherical microphone array.	A hemi-anechoic chamber was used for the field experiment.
Kim et al., 2019 [66]			×		The unsteady Reynolds-averaged Navier–Stokes (uRANS) equations were solved to investigate the steady and unsteady loading noise sources around the blades with a radius of 17 cm rotating at 5000 rpm.	The three-dimensional uRANS simulation result was compared with data from NASA's experiment.
Lotinga et al., 2023 [67]		×			Review and discuss the current state of UAS noise measurement and assessment practices.	Review
Langen et al., 2022 [26]		×			A conceptual framework for UAS noise in U-Space architecture with a use case scenario and verification method.	Simulation
Jung et al., 2024 [22]			×		An investigation on blade skew effect on interaction tones by a contra-rotating UAS.	CFD simulation and experiment in an anechoic chamber.
Arona et al., 2018 [45]				×	The acoustic properties of sUAS with low ambient noise conditions are assessed using sound equivalent level (Leq) with a calibrated U-MIK 1 and a 1/3 octave band soundscape approach.	Field experiment recorded acoustic data using a calibratedUMIK-1 and connected to an Apple iPad running Faber Acoustical SoundMeter Pro.
Jiang et al., 2021 [21]	×				A boundary element method (BEM)-based solver is employed to evaluate the scattering of rotor noise of UAS fuselage.	Simulation
Liu et al., 2021 [16]	×				A remolded acoustic energy decay model preserved in acoustic energy attenuation inverse of distance square was used to generate training data for UAS localization.	Simulation
Ramos-Romero et al., 2022 [13]		×			A modeling framework for setting recommendations for UAS operations to minimize community noise impact.	An acoustics database is referred from Volpe [68].
Bian et al., 2021 [69]	×				An in-house solver, Environmental Acoustic Ray-Tracing Code (EnvARC), was used to investigate noise UAS noise impact.	Simulation
Tan et al., 2023 [27]	×				The noise impact of delivery drones in an urban community is assessed using an efficient Gaussian bean tracing method.	Simulation
Choi et al., 2023 [70]			×		A method for predicting rotor UAV *aeroacoustic* noise considering bending–torsion coupling.	Simulation
Mankbadi et al., 2021 [71]				×	High-fidelity simulations of unsteady flow and radiated rotor UAS noise were conducted to capture the broad-band noise associated with the propeller and its wake.	Computational simulations on the dilatation field, the Lighthill's stress tensor, and each term in the Ffowcs Williams–Hawking's integral solution of the far field.
Ren and Cheng, 2020 [11]	×				Noise impact was assessed and integrated into a comprehensive third-party risk index model of UAS urban logistics.	Field experiments and simulations.
Ivoševi'c et al., 2021 [72]		×			UAS noise measurement and survey were conducted for a comparative analysis of two UAS's different performances.	Field experiments and surveys on human subjects.

Table 7. *Cont.*

Literature (Ref.)	Region				Problem Solving and Innovation	Method
	CN	EU	Others	US		
Jung et al., 2023 [73]			×		The interaction tones produced by the periodic unsteadying loading on the blades of two different contra-rotating UAS were studied.	CFD simulations and experimental measurements showed generally good agreement.
Škultéty et al., 2023 [12]		×			An assessment of *psychoacoustic* UAS noise impact in several weight categories concerning the urban environment.	Field experiments and simulations.
Han et al., 2020 [50]			×		An innovative rotation per minute (RPM) fluctuation correction method considering the frequency modulation effects was developed.	Field experiments and simulations.
Kapoor et al., 2021 [74]			×		A review of current state of manned and unmanned aircraft noise assessment and mitigation approaches.	Review
Christiansen et al., 2020 [75]		×	×	×	UAS noise impact on marine mammals was examined.	Acoustic cue perceptibility of UAS noise was examined by measuring the received UAS underwater noise level on whales equipped with acoustic tags (DTAGs).
Christiansen et al., 2016 [41]		×	×		UAS noise underwater levels on marine mammals were measured to assess potential impact on marine mammals.	In-air and in-water noise from two common UAS were measured.
Hui et al., 2021 [76]			×		An evaluation on human perception of four rotor UAS.	Field experiments and surveys on human subjects.
Augustine and Burchfield, 2022 [77]				×	A preliminary study of rotor UAS noise impact on wildlife.	Field experiments.
Park et al., 2017 [78]			×		A noise prediction method for a ducted fan UAS with complicated geometry.	Experiments and simulations for aerodynamic analysis and noise prediction.
Lee and Lee, 2020 [42]			×		A study on mutual rotor-to-rotor interactional effects on the aerodynamic performance, wake structure, and *aeroacoustics*.	CFD simulation results were compared to the NASA experimental data.
Schäffer et al., 2021 [44]		×			A systematic review on drone noise emissions and noise effects on humans.	Review
Stephenson et al., 2019 [36]				×	Identifying effects of flow recirculation on an isolated rotor's acoustic emissions in a closed anechoic chamber.	Indoor experiment
Tinney and Sirohi, 2018 [23]				×	A first-principles understanding of the sound field produced by UAS in hover was presented.	Indoor experiment
Torija et al., 2021 [47]	×	×			Investigating the optimal rotor spacing distance configuration to minimize noise annoyance	Indoor experiment
Torija and Clark, 2021 [46]		×			The state-of-the-art evidence on human response to aircraft noise was reviewed, and its application for UAS was discussed.	Review
Torija et al., 2020 [10]	×	×			A series of audiovisual scenarios was created to investigate the effects of UAS noise on the reported *psychoacoustic* metrics of seven different types of urban soundscapes.	The outdoor field recorded audio-visual data, generating stimuli used for the experiment.
Zhong et al., 2020 [79]	×				An asymptotic analysis of the frequency-domain formulation to compute the tonal noise of UAS	Indoor experiments and simulations
Kloet et al., 2017 [37]			×		An acoustic signature profile of a sUAS was generated.	Outdoor field experiments and indoor laboratory testing

3.2.1. Aeroacoustics

Aeroacoustics is commonly associated with aerodynamic analysis, which considers various types of rotor/propeller design, control, and operation of UAS platforms. These analyses are usually conducted in outdoor/indoor experiments or computational fluid dynamics simulations.

The noise a rotor emits in the transitional boundary layer regime is similar to the airfoil case. The Lattice–Boltzmann method (LBM) is the most common approach to statistically tracking the advection and collision of fluid particles [48].

The majority of the reviewed studies specifically investigate UAS aeroacoustic noise measurement, considering different types of UASs [19,52,65], certain UASs with different RPM [62] and pitch controls [24], and plenty of studies focused on hovering and static thrust only [23,78]. Specifically, Han et al. [73], Jung et al. [22,72], Wu et al. [56], Casalino et al. [20,43,48], Jiang et al., [21,57], Kim et al. [66], Mankbadi et al. [71], Choi et al. [70], Lee and Lee [42], Stephenson et al. [36], and Zhong et al. [79] investigate aerodynamics and aeroacoustics of rotor UAS, considering different designs and conditions of the propeller. Go et al. [64] and Park et al. [78] investigate the tonal noise from a rigid shroud-equipped UAS. The prediction of aeroacoustic noise effects from UAS swarms is studied by Dbouk and Drikakis [61]. Notably, measuring UAS noise also facilitates the detection, identification, classification [15], and localization [16] of illegal UAS operations.

3.2.2. Psychoacoustics

In many cases, aeroacoustic metrics, such as sound pressure levels (SPLs), might not reflect all features of the radiated noise, especially when human perception is of interest [65]. Therefore, psychoacoustic surveys from UAS operations, considering hovering [67], takeoff and landing [46,47], etc., have become common trends in studying the human response to UAS noise. The annoyance caused by UAS can be influenced by loudness, tonality, sharpness, fluctuation strength, and roughness [35]. Psychoacoustics metrics computed using the reconstructed sound pressure field indicated good agreement between the target and propagated signal [65].

Human subjects are recruited and involved in experiencing various types of UAS sounds, depending on the purpose of the study. Gwak et al. [35] unveil the correlation between the annoyance level and the size of drones, emphasizing the significant contributing factors, including sharpness, loudness, and fluctuation.

Several studies integrate the noise impact into a comprehensive framework to assess the overall community impact [10,11,46,47]. For instance, Torija et al. [10] discussed the effect of ambient road traffic noise in masking UAS noise, as it might shed light on strategies to optimize UAS path planning in UAM.

3.2.3. Other Findings

Notably, the issue of UAS noise has garnered significant attention from various interdisciplinary domains. Wildlife biologists, for instance, use UASs to monitor wildlife, leading to numerous studies on the impact of UAS noise on wildlife. These studies document birds' reactions to UASs [77], compare UAS noise with ambient sounds [77], analyze underwater aeroacoustic metrics [41], and investigate changes in horizontal behavior and surfacing patterns [75].

The predominant focus in the reviewed literature has been on rotor UAS, though Arona et al. [45] have conducted assessments of fixed-wing UAS noise. Field experiments include outdoor testing and recording with selected UAS, while indoor experiments are typically performed in closed anechoic chambers. Zhou et al. [60] concentrated on rotor noise features using microphone arrays and conventional beamforming algorithms. Tan et al. [27] developed an economical approach for UAS flight simulation and noise assessment for delivery drones in urban communities, utilizing the Gaussian beam tracing method to compute sound propagation in complex environments accurately and efficiently.

An innovative study by Utebayeva et al. [58] employs a range of machine learning (ML) models, such as Simple Recurrent Neural Networks (SimpleRNNs), Long short-term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM), and Gated Recurrent Unit (GRU) architectures. This study suggests that ML algorithms could offer a promising pathway for assessing and predicting UAS noise.

Figure 6 presents an author keyword cloud generated based on the frequency of author keywords. There are a total of 116 occurrences of 50 different keywords. The top ten author keywords by frequency are 'aeroacoustics' (7), 'drone noise' (7), 'drones' (7), 'propeller noise' (7), 'noise' (6), 'unmanned aerial vehicle' (6), 'drone' (5), and 'rotor noise' (5).

Figure 6. Author keyword cloud.

4. Discussion

4.1. General

One notable feature is the lack of international collaborations in UAS noise-related studies, as evidenced in Figures 3 and 4. This can be attributed to the relative immaturity and ongoing growth of the UAS industry compared to the manned aircraft industry. The level of maturity, market size, and policies and regulations vary and are still evolving across different countries. Nonetheless, fostering such connections should be a priority of individual governments and international organizations, such as the International Civil Aviation Organization (ICAO) and the Association for Uncrewed Vehicle Systems International (AUVSI), as the mission and vision of UAS are integrated into Advanced Air Mobility (AAM) initiatives [9].

Utebayeva et al. [58] highlight the need to expand the audio dataset of loaded UAS and explore distance-based detection challenges. Furthermore, developing a publicly available benchmark UAS dataset would enhance simulation-based noise assessment and prediction, akin to the Aircraft Noise and Performance (ANP) database developed and maintained by EASA [80].

Extensive research has demonstrated the feasibility and cost-effectiveness of a data-fusion-based approach in traditional manned aircraft noise prediction [81–83]. Similarly, this approach could benefit UAS noise impact assessment by leveraging telemetry data broadcasted by UAS. For instance, the FAA mandates that sUAS operating in the USA must be equipped with remote identification, also known as Remote ID, which includes time-location and fleet information [84]. Despite the limitations in current UAS surveillance capabilities, these advancements will highlight the potential for data-fusion applications in future active UAS noise monitoring, assessment, and prediction. A roadmap is presented in Figure 7.

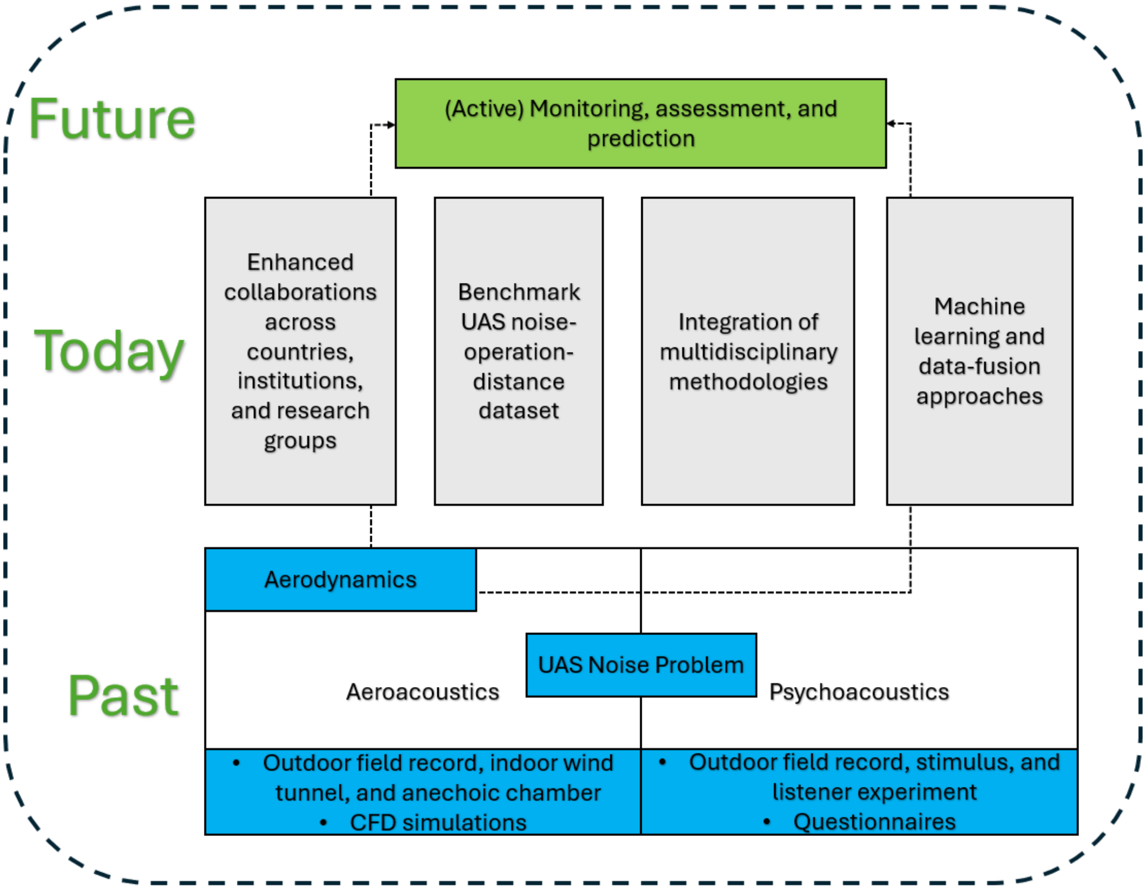

Figure 7. A new (active) UAS noise monitoring, assessment, and prediction framework.

4.2. Aeroacoustics

This review covers the past ten years of literature, aligning with the rapid development and penetration of UASs. The aeroacoustic-related studies reviewed heavily focus on traditional aerodynamics and aeroacoustics fields, typically based on the foundations of conventional manned helicopters [18]. This suggests a more expansive search window could capture more relevant literature and unveil additional insights. Despite the limitations of this review, UAS aeroacoustics measurement has been extensively studied through laboratory and field experiments, considering sound level, frequency, and directivity. Section 3.1.3. suggests that enhanced collaboration across countries, institutions, and research groups could facilitate the development of a benchmark UAS noise-to-operation-to-distance dataset, thereby benefiting stakeholders' decision-making in regulatory and certification development, active UAS noise abatement policies, etc.

4.3. Psychoacoustics

Compared to aeroacoustics studies, there are limited studies on *psychoacoustic* analysis regarding human responses to UAS noise [10,12,72], which can be enhanced when multidisciplinary methodologies are well-designed in specific scenarios. On the other hand, innovative techniques, such as machine learning and data-fusion techniques, might facilitate active UAS noise monitoring, assessment, and prediction from a practical standpoint. Since UAS fleet mix and performance directly correlate with psychoacoustic metrics, further research could provide deeper insights and reveal correlations between community annoyance and UAS fleet characteristics and performance. Such insights are crucial for planning low-altitude flights in urban environments and supporting stakeholders' decision-making. Beyond the scientific rigor of traditional acoustic measures reviewed in this literature, an emerging area that leverages data science and multisensory approaches shows promising short-term applications [58].

5. Conclusions

Aircraft noise has long been a concern for various stakeholders, as its negative environmental impact can lead to adverse attitudes from local communities toward airport operations and planning. With the increasing use of unmanned aerial systems (UAS) in civil and commercial domains, it is essential to study UAS-induced noise. This study applies bibliometric and citation analysis to related literature from 2015 to 2024, sourced from the Web of Science Core Collection database. The current progress in UAS noise monitoring, assessment, and prediction has been systematically reviewed and presented through a comprehensive visualized framework. This review also highlighted the critical limitations and challenges in the field, such as the gap in a comprehensive benchmark UAS noise database, the need for advanced data-fusion techniques, and the integration of diverse data sources. These insights unveil significant opportunities for future research, particularly in developing more sophisticated noise prediction models, real-time monitoring systems, and realistic exposure–response assessment frameworks [67].

As UASs proliferate across civil and commercial sectors, understanding and mitigating their noise impact becomes increasingly vital. Integrating remote identification (Remote ID) data and other telemetry information presents a promising avenue for enhancing UAS noise assessment. Furthermore, enhancing international collaboration among academic institutions, industry stakeholders, and regulatory bodies will be essential in driving innovations and establishing robust noise management frameworks.

This review serves as a cornerstone for UAS noise research, providing a foundational understanding and a roadmap for future investigations. By addressing the identified challenges, leveraging emerging technologies, and fostering collaborations, the field can move towards more effective noise abatement strategies, ultimately contributing to the broader acceptance and sustainable integration of UAS into various aspects of society.

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Abbreviations

The following abbreviations are used in this manuscript:

AAM	Advanced Air Mobility
ADS-B	Automatic Dependent Surveillance-Broadcast
AUVSI	Association for Uncrewed Vehicle Systems International
BiLSTM	Bidirectional Long Short-Term Memory
CAA	Computational Aeroacoustics
CFD	Computational fluid dynamics

DDES	Detached eddy simulation
FAA	Federal Aviation Administration (USA)
GA	General Aviation
GRU	Gated Recurrent Unit
ICAO	International Civil Aviation Organization
LBM	Lattice Boltzmann Method
LSTM	Long Short-Term Memory
NASA	National Aeronautics and Space Administration
RANS	Reynolds-averaged Navier–Stokes models
RPM	Rotation per minute
SimpleRNN	Simple Recurrent Neural Networks
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
UAM	Urban Air Mobility
UAS	Unmanned Aerial System/ Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle/Uncrewed Aerial Vehicle
VTOL	Vertical Takeoff and Landing Aircraft

Appendix A

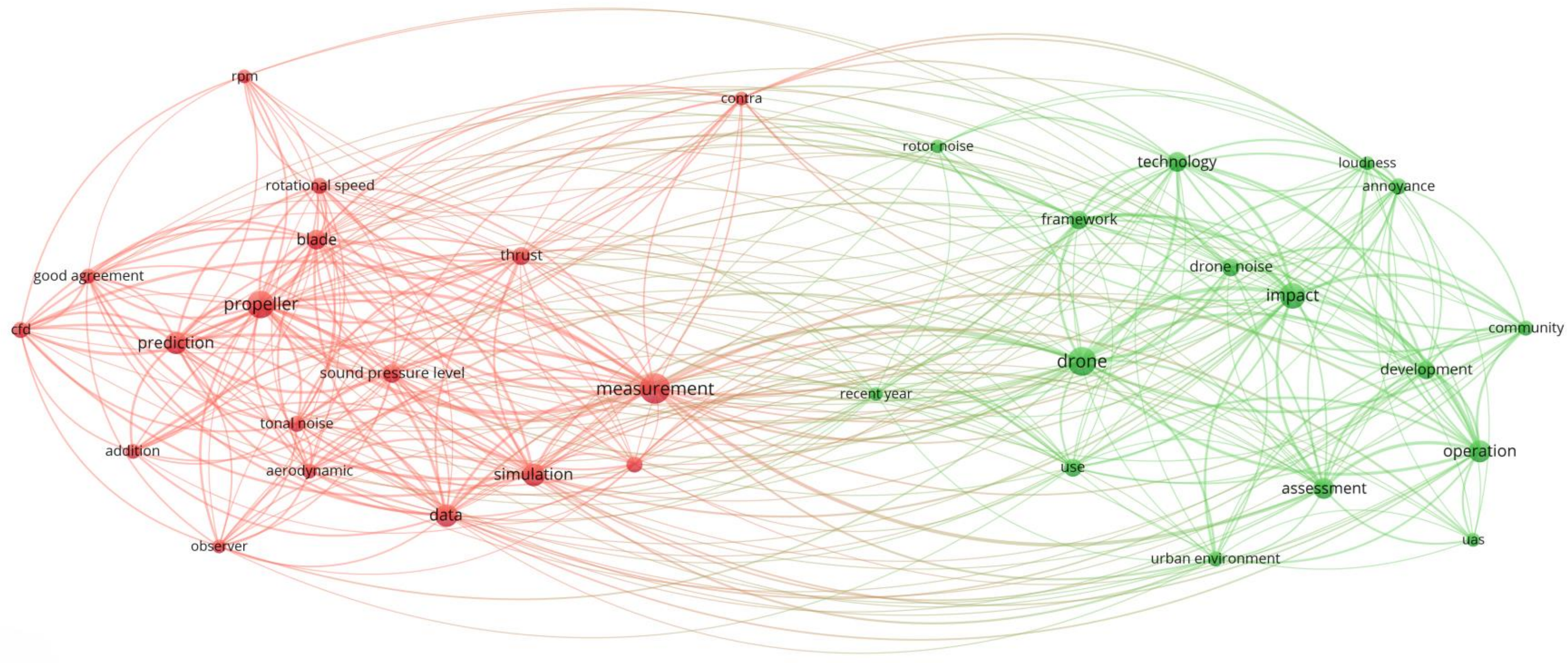

Figure A1. Co-occurrence network of topics (Title and Abstract).

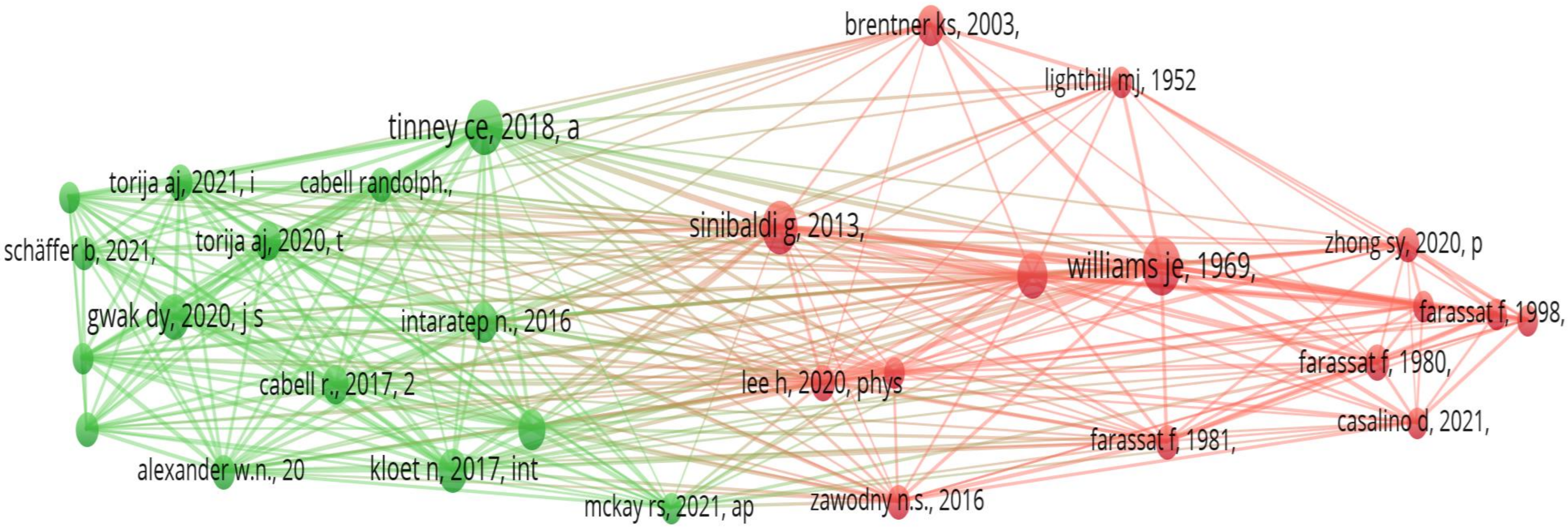

Figure A2. Network visualization of co-citation (fractional counting).

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