

Overcoming software bottlenecks for scalable passive acoustic monitoring: A survey-informed expert consensus

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ABSTRACT

Passive acoustic monitoring (PAM) enables minimally invasive sampling of wildlife across broad spatial, temporal and taxonomic scales. Its ongoing and widespread use has generated unprecedented volumes of acoustic data, shifting the primary bottleneck from data collection to the storage, processing, integration, and interpretation of PAM outputs. Although many software tools exist to address these challenges, differences in their design, scope, and usability often result in fragmented, complex analytical workflows. To identify the key barriers and opportunities shaping the implementation of PAM surveys, we conducted a structured, community-informed consultation developed through iterative engagement, comprising international practitioners working across terrestrial and aquatic ecosystems. Thirty experts identified and ranked their most critical bottlenecks in current PAM workflows, spanning data storage, processing, and interpretation. The top challenge identified related to accurate species identification using deep learning and artificial intelligence (AI) models, especially in noisy soundscapes or for underrepresented taxa. Eight additional priority challenges included workflow fragmentation, limited availability of user-friendly analytical and visualisation tools, uneven access to software, manual validation bottlenecks, computational constraints, and difficulties in data handling, standardisation, and sharing. Using a follow-up consultation with 24 of the original 30 experts, we propose practical mitigation strategies for these priority challenges, supported by step-by-step guidance to help overcome key barriers. Together, these insights provide a roadmap toward more scalable, open-access, and collaborative software systems, which are increasingly essential to realise the full potential of PAM in global biodiversity monitoring.

1. Introduction

Global biodiversity is under threat, with ecosystems facing rapid declines in species richness and ecological stability (Tilman et al., 2017). Monitoring biodiversity at large scales is critical for tracking ecological change, informing conservation and restoration management, evaluating protected areas, and supporting national biodiversity reporting (Pereira and Cooper, 2006). Passive Acoustic Monitoring (PAM) has become a robust and cost-effective solution for biodiversity monitoring, capturing wildlife sounds over extended periods to provide a non-invasive and scalable approach across diverse environments (Darras et al., 2025; Gibb et al., 2019). The integration of artificial intelligence (AI), and more specifically, deep learning algorithms, has further accelerated PAM adoption by enabling automated identification of target sounds in large audio datasets (Gibb et al., 2019). Yet, as PAM applications expand, so too do the challenges of storing, analysing, integrating, and interpreting the vast amount of data they generate (Gibb et al., 2019).

The affordability and performance of hardware for PAM surveys have significantly improved in recent years, marking a major milestone for its scalability (Sheng et al., 2019). Early adoption of PAM relied on a limited choice of commercial recorders, which, although reliable, had a cost exceeding USD 1000 per terrestrial unit and several thousand per aquatic unit (Browning et al., 2017). These costs constrained adoption, particularly in resource-limited contexts and large-scale monitoring programs. The emergence of lower-cost devices such as AudioMoth (Hill et al., 2018) and Song Meter Micro (Wildlife Acoustics, USA) has increased accessibility for PAM, particularly for terrestrial applications, with unit costs now commonly around USD 100–150 (Gibb et al., 2018; Hill et al., 2018; Lamont et al., 2022). This hardware transition enables unprecedented data collection across large spatial and temporal scales (Hoefer et al., 2023; Stowell and Sueur, 2020; Sugai et al., 2019). As a result, the primary bottleneck in PAM has shifted from data acquisition to data management, analysis, and interpretation (Gibb et al., 2019).

In parallel with rapid advances in PAM hardware, the quantity, complexity, and diversity of acoustic data being generated have increased dramatically. However, these advances have not been matched by equivalent progress in the software tools required to store, manage, share, analyse, validate, and interpret large PAM datasets.

Major progress has been made in automated detection and classification, particularly through the rise of deep learning and foundation bio-acoustic models (Hamer et al., 2023; Kahl et al., 2021; van Merriënboer et al., 2025). But in practice, PAM users must navigate a fragmented landscape of tools for data storage, metadata integration, species detection, manual validation, visualisation, and reporting, often across different programming languages, file formats, and platforms (Hanf-Dressler et al., 2026). Although some web-based platforms now offer cloud storage and collaborative features (e.g., Aide et al., 2013; Darras et al., 2024), many workflows still rely on ad hoc combinations of software that are difficult to scale, transfer, and maintain across projects and user groups. As a result, despite clear technological progress, software-related barriers continue to limit the efficiency, reproducibility, and widespread adoption of PAM in biodiversity monitoring.

Although previous studies have recognised that software has become the principal bottleneck for scalable PAM (e.g., Gibb et al., 2019), there has been no systematic effort to identify, prioritise, and synthesise these challenges across the full workflow, nor to translate them into practical guidance for researchers and practitioners. To address this gap, we employed a structured expert consultation to identify key technical and practical barriers that limit the scalability, accessibility, and reproducibility of PAM analyses for biodiversity monitoring. Our focus is on the software infrastructure and analytical workflows underpinning PAM, rather than on the ecological metrics ultimately derived from acoustic data (e.g., species richness, occupancy, or relative abundance). Open-ended responses were scored and ranked to prioritise the bottlenecks perceived as most limiting by practitioners. We first synthesise the dominant challenges reported by the community, spanning species identification, fragmented analytical workflows, data handling, validation, and standardisation. Second, we summarise expert-endorsed strategies currently used to mitigate these barriers, highlighting practical tools and approaches already available. Third, we translate these insights into a set of practical guides provided as Supplementary Material to support implementation in real-world PAM workflows (see Box 1). Finally, we outline how emerging developments, such as edge computing, cloud-based processing, and citizen science integration, can offer transformative solutions to scale PAM globally. These insights provide a roadmap for improving the software infrastructure and analytical workflows required for scalable passive acoustic monitoring.

Box 1 Practical guides provided as Supplementary Material.

To translate the outcomes of the expert consultation into actionable resources, we provide a series of practical guides as Supplementary Material (Guides). Each guide addresses a specific software or workflow challenge commonly encountered in large-scale passive acoustic monitoring (PAM) and illustrates feasible solutions using currently available tools and approaches.

Guide 1. Expanding BirdNET models to non-avian species through transfer learning: Using a case study of a multi-species frog classifier, it demonstrates how an existing CNN platform can be repurposed to detect non-avian taxa using transfer learning, enabling the development of custom classifiers from relatively small, taxon-specific training datasets.

Guide 2. Building acoustic classifiers with little or no labelled training data: Introduces embedding-based and clustering approaches that allow researchers to discover, curate, and label recurrent sound types directly from unlabelled recordings, supporting classifier development in data-poor systems.

Guide 3. Data augmentation in PAM workflows: Reviews dataset-level and signal-level data augmentation strategies that improve classifier robustness and generalisation, with practical guidance on when and how to apply augmentation in bioacoustic contexts.

Guide 4. Accounting for classifier errors to make correct ecological inferences: Presents statistical and validation-based strategies for managing false positives and false negatives in automated detector outputs, ensuring that ecological inferences remain robust and defensible.

Guide 5. Coding an integrated multi-tool workflow in R: Provides a step-by-step framework for building reproducible, end-to-end PAM pipelines in R, integrating audio handling, detection, classification, validation, and visualisation across multiple tools.

Guide 6. Developing GUI-based interfaces for PAM: Explores how graphical user interfaces can lower technical barriers to PAM by supporting tasks such as validation, annotation, threshold selection, and exploratory analysis without requiring coding expertise.

Guide 7. Using metadata standards for acoustic data management: Outlines best practices for structuring and documenting PAM datasets using hierarchical metadata, drawing on existing biodiversity standards to improve data interoperability, reuse, and long-term value.

Guide 8. Reproducible scientific workflows for PAM: Describes practical approaches to ensuring transparency and reproducibility in PAM research, with a focus on version control, documentation, open-source tools, and collaborative platforms such as Git and GitHub.

2. Material and methods

We followed a structured, iterative, anonymous, and multi-round consultation process. The study comprised five sequential stages: (1) expert identification, (2) initial expert consultation, (3) analysis and prioritisation of bottlenecks, (4) follow-up consultation on strategies, and (5) synthesis and validation (Table 1).

Research was conducted as a collaborative research process, with all participating experts contributing as formal collaborators and active co-authors of this manuscript. In accordance with institutional guidelines, this form of collaborative research did not require formal ethics approval. All contributions from the co-authors were voluntary, non-sensitive in nature, and collected anonymously.

2.1. Expert identification

The core team (MEM, CPG, KB, and MP) compiled an initial list of PAM specialists using the Web of Science Core Collection. The search was conducted on 4 June 2025 using the search string in the “Topic” field: “passive acoustic monitoring” OR “bioacoustics” OR “ecoacoustics” OR “acoustic indices” OR “soundscape ecology”. Results were restricted to publications from 2014 to 2024. Authors were ranked according to the citations accrued by publications returned through this search, and the initial list comprised the 100 most-cited researchers who had authored at least five peer-reviewed publications within the resulting literature.

This list was subsequently expanded through purposive and snowball sampling, incorporating additional specialists identified through collaborator recommendations, recognised involvement in major PAM projects, monitoring programs, and software development initiatives, and to improve representation across taxa, ecosystems, sectors, and geographic regions. This approach was intended to broaden the diversity of expertise represented in the consultation rather than to produce a statistically representative sample.

The final invitation list comprised 156 experts, who were contacted via email by MEM and CPG between the 9th and the 13th June 2025. The invitation email highlighted the opportunity for experts to volunteer

as colleagues and collaborators, participating in the consultation process and the collective development of the resulting manuscript.

2.2. Initial expert consultation: identifying and prioritising bottlenecks

We conducted an expert consultation through an online semi-structured questionnaire comprising 10 questions (see Supplementary Material Questionnaire SMQ1), designed to capture both quantitative and qualitative data on current practices and challenges in PAM. The questionnaire was structured into three components:

- **Background information:** This section captured participants' domain expertise (e.g., birds, marine mammals), years of experience, geographic and environmental focus, and professional role.
- **Hardware and software usage:** This component collected data on the types of PAM hardware and software used, including specific tools for species identification, metadata management, and AI model deployment.
- **Bottlenecks:** Respondents were asked to write (max one sentence length) and rank in order of importance their top five challenges for processing PAM data, including storage, annotation, analyses, and validation.

The survey instrument was developed in the Qualtrics platform and piloted internally by the core team (MEM, CPG, KB, and MP) to ensure clarity and relevance. It was administered online and distributed via email between the 9th and the 25th of June 2025. Participation was voluntary, and responses were anonymous unless participants opted to provide contact details for follow-up engagement or co-authorship in subsequent outputs. Participants could skip questions, leading to variation in response counts across items. A total of 30 respondents completed the initial survey.

2.3. Analysis and prioritisation of bottlenecks

Qualitative and quantitative analyses were undertaken to identify, synthesise, and prioritise key challenges in PAM workflows. Qualitative

responses to open-ended questions were analysed using an inductive thematic approach. Challenges were grouped based on conceptual similarity, with overlapping points merged and terminology standardised. Coding and categorisation were initially conducted by MEM and then refined through discussion with the core team until agreement was reached. From the initial expert consultation ($n = 30$), we identified nine overarching themes derived from 122 individual text entries describing key bottlenecks in PAM workflows (see Supplementary Material Questionnaires SMQ2 for the categorisation of responses). This synthesised set of themes was then shared with 30 PAM experts who had opted to provide contact details for follow-up engagement on the 1st of August 2025 for validation (stage 5; see 4.5. Final Synthesis and Validation). This ensured that the final categories were complete and accurately represented the bottlenecks identified during the initial consultation.

Quantitative analysis was undertaken to identify the most consistently prioritised challenges across respondents. Experts were asked to list up to five key challenges related to software solutions for analysing audio recordings in PAM and to rank them in order of priority. Each response was assigned a score from 5 (bottleneck identified as the highest priority) to 1 (lowest priority). For each theme, a total score was calculated by summing the values provided across all respondents. This scoring approach captures both the frequency with which a bottleneck was identified and its relative importance within individual responses.

These scores represent aggregated perceptions within the cohort of the initial expert consultation rather than independent measurements or standardised effect sizes. Differences between scores should therefore be interpreted as relative differences in perceived importance within this group, rather than as precise or statistically comparable quantities.

2.4. Follow-up expert consultation: strategies to minimise bottlenecks

The core team (MEM, CPG, KB, and MP) developed a second survey to identify practical strategies for addressing the nine challenges identified in the initial expert consultation (see Supplementary Material Questionnaire SMQ3). The online Qualtrics survey was distributed on the 11th of August 2025 via email by CPG to the 30 PAM experts who participated in the initial consultation. A total of 24 experts completed the follow-up survey.

The survey comprised two open-ended sections designed to elicit both current practices and future-oriented solutions for each challenge. For each bottleneck, experts were asked:

1. What tips or tools do you recommend to deal with this pain point?
2. What would an ideal future solution look like?

Table 1

Overview of the expert consultation, synthesis, and validation process used to identify PAM workflow bottlenecks and proposed strategies.

Stage	Purpose	Participants	Input	Output	Role
1. Expert identification and invitation	Build a broad invitation list of PAM specialists	156 experts invited	Web of Science search, snowball sampling, recommendations	Invitation list	Defines the sampling frame
2. Initial expert consultation	Identify and rank the main bottlenecks in PAM workflows	30 respondents	Semi-structured Qualtrics survey	Raw quantitative and qualitative responses	Provides evidence for current bottlenecks in PAM
3. Analysis and prioritisation of bottlenecks	Consolidate open-ended responses into a clear set of core challenges	Core team synthesis; then validation by the 30 initial respondents	Open-ended bottleneck responses and participant rankings	Nine consolidated bottlenecks, validated by the initial respondent group	Bottlenecks are organised in themes with relative severity
4. Follow-up expert consultation on strategies	Identify current practices and future-oriented solutions	24 participants from the original 30 respondents	Second Qualtrics survey asking existing tools and emerging opportunities and future directions	Qualitative responses on current and proposed strategies for each bottleneck	Provides the expert-derived “emerging opportunities and future directions”
5. Final synthesis and approval	Refine strategies, identify gaps, and reach agreement on final recommendations	Core team synthesis; validation by the 24 s-survey participants	Follow-up survey responses and email-based validation feedback	Final set of recommended strategies, with current solutions, future priorities, and case studies	Provides the final interpretive synthesis presented in the Discussion, recommendations, and Box 1

This stage was intentionally qualitative, focusing on capturing expert perspectives, experiences, and proposed directions rather than generating quantitative comparisons. To minimise ordering bias, the list of identified bottlenecks was randomised for each participant.

2.5. Final synthesis and validation

Responses were analysed using an iterative qualitative synthesis approach. The core team (MEM, CPG, KB, and MP) reviewed the responses, standardising terminology and removing redundancies. The resulting synthesis was circulated on the 20th of October 2025 via email by MEM to the 24 PAM experts who completed the second survey. Experts were invited to validate the synthesis, suggest refinements, and identify any gaps or overlooked areas. Through this iterative and collaborative feedback process, the expert group reached consensus on a final set of recommended strategies to address each bottleneck, including both current practices and future-oriented solutions. We provide illustrative case studies of existing practices or tools to address each challenge identified (see [Box 1](#)).

All co-authors (i.e., participating experts) reviewed and approved the final list of bottlenecks and proposed solutions, ensuring shared ownership and alignment with community needs. Co-authorship was based on voluntary participation in this collaborative research process, which may have influenced the framing and emphasis of the final outputs.

3. Demographic overview of survey respondents

Of the 156 PAM experts invited to complete the survey, we received responses from 30 experts during the initial consultation. Although the invitation process aimed to capture broad representation across sectors, regions, ecosystem types, and taxonomic expertise, participation was voluntary, and not all research groups or perspectives were ultimately represented. Consequently, the respondent cohort should be interpreted as a self-selected subset of the broader PAM community rather than a comprehensive or exhaustive sample.

Respondents represented researchers and practitioners working across terrestrial, freshwater, and marine ecosystems, spanning applications such as biodiversity monitoring, ecological research, conservation management, and software development. Most respondents were academic researchers (87%), with the remaining from industry or from government agencies. The majority of experts had more than 8 years of experience (80%), followed by 4–7 years (14%) and 1–3 years (6%). In terms of geographic region where the experts have conducted work, the survey captured input from all continents ([Fig. 1](#)). Respondents have collected data in Europe (31%), South America (25%), North America

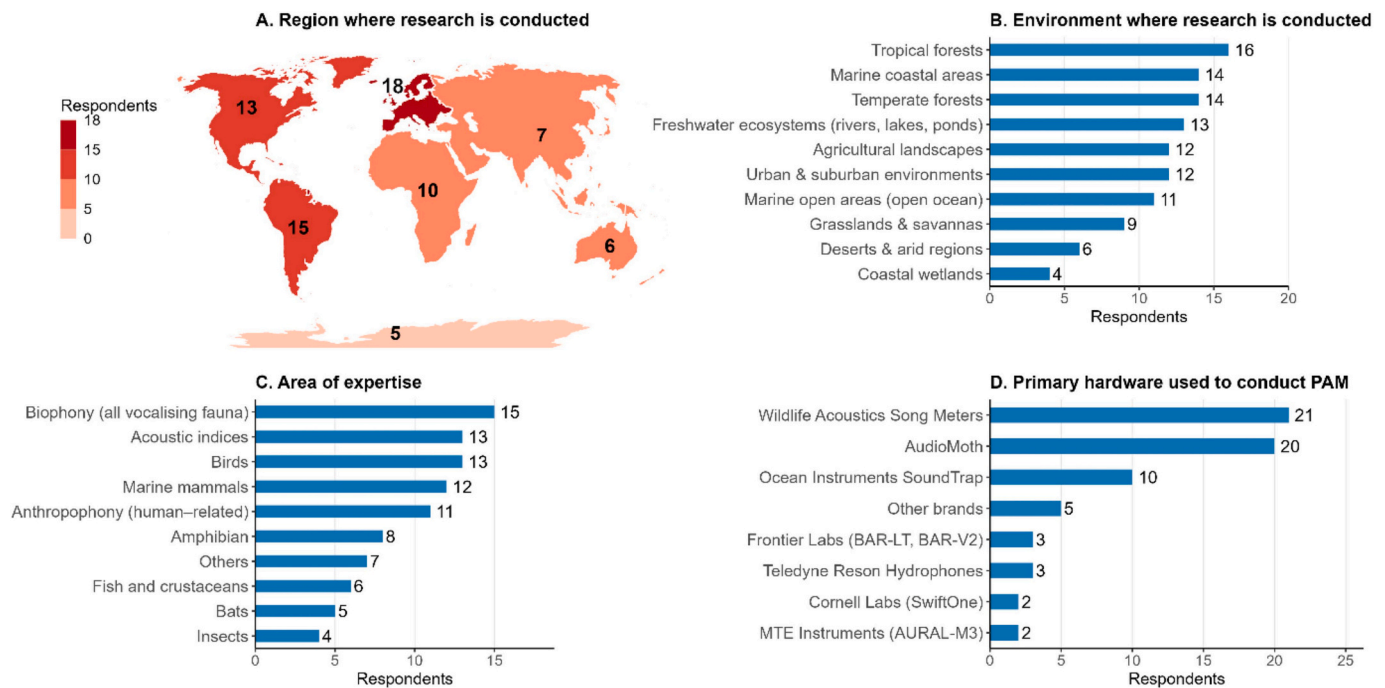


Fig. 1. Characteristics of survey respondents in the initial expert consultation ($n = 30$), including geographic regions (A), research environments (B), areas of expertise (C) and hardware types used (D). Values indicate the number of respondents selecting each category; multiples selections were allowed.

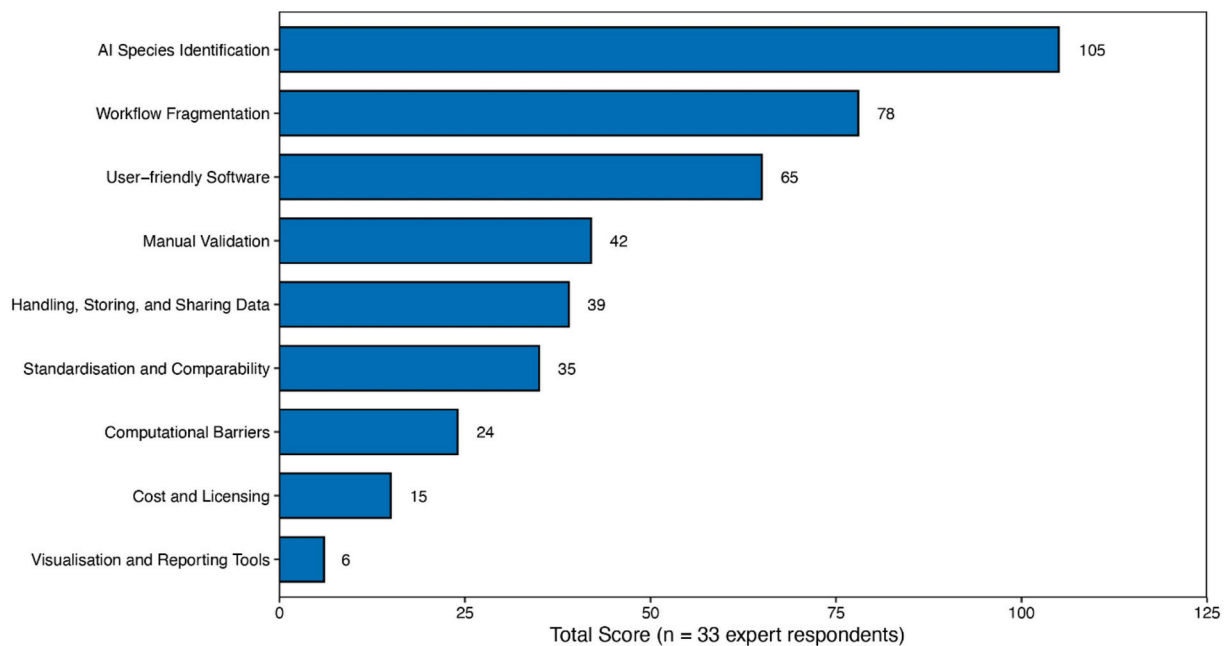


Fig. 2. Total perceived importance of key bottlenecks in passive acoustic monitoring (PAM) workflows identified in the initial expert consultation ($n = 30$ respondents). Each bar represents the total score for each bottleneck, weighted from 5 (highest priority) to 1 (lowest priority) according to respondents' rankings. Categories are ordered by total score from highest to lowest. See Table 2 for more details on each bottleneck.

(22%), Africa (17%), Asia (12%), Australia & Oceania (11%), and Polar Regions (8%) (Fig. 1A). Across realms, a larger number of experts worked mainly in terrestrial ecosystems (55%), followed by marine environments (30%) and freshwater systems (15%; Fig. 1B).

Expertise was most frequently reported for biophony (15.9%), avian monitoring (13.8%), and marine mammal monitoring (12.8%), amphibians (8.5%), fish and crustaceans (6.4%), bats (5.3%), and insects (4.3%; Fig. 1C). Several respondents also reported experience with terrestrial mammals, including primates and large carnivores (2.1%).

Beyond taxon-specific applications, a substantial proportion of expertise is related to soundscape and analytical domains, including acoustic indices (13.8%), anthropophony (11.7%), and geophony (3.2%). Finally, two respondents identified themselves as software developers and taxonomic bioacousticians (Fig. 1C).

When it comes to PAM hardware, Wildlife Acoustics Song Meters (33%) and AudioMoth devices (31%) emerged as the most widely used (Fig. 1D). Other devices cited were the Ocean Instruments SoundTraps (16%), for underwater applications, followed by devices from Frontier

Table 2

Summary of key bottlenecks in passive acoustic monitoring (PAM) workflows (ordered by their importance), with corresponding short descriptions, current strategies reported by experts, and envisioned ideal future solutions. See Fig. 2 for a bar graph of bottlenecks.

Bottleneck	Score	Summary	Current Solutions	Emerging Opportunities
AI Species Identification	105	Current AI models can be limited in taxonomic and geographic scope; lack of annotated datasets hinders progress.	Combine AI with manual validation; train region-specific models (e.g., BirdNET transfer learning); use data augmentation; apply statistical filters; share annotated datasets and code. Manually stitch tools together; use R/Python pipelines; modular platforms (Arbimon, PAMGuard, Raven, EcoSoundWeb); enforce metadata/file standards; Standard Operating Procedures (SOPs) for reproducibility.	Globally diverse, open-access datasets; explainable, generalisable AI models; transparent uncertainty metrics; collaborative platforms for model- and dataset-sharing.
Workflow Fragmentation	78	Tools are disconnected and rarely interoperable, creating inefficiencies, errors, and difficulties scaling across projects or taxa.	GUIs like BirdNET, Raven, Arbimon, PAMGuard, Kaleidoscope, WildTrax; combine with R/Python scripts, Shiny Apps, workshops; collaborate with computer scientists.	Fully integrated, modular PAM platform; universal annotation/metadata standards; cloud-based scalable systems; one-stop, open-access acoustic monitoring hub.
User-Friendly Software	65	Many tools have steep learning curves, require coding skills, or are designed for specific taxa, excluding many ecologists.		Intuitive, GUI-based open-access platforms covering full workflows; modular, cross-taxon, cloud dashboards; explainable AI built into user interfaces.
Manual Validation	42	Checking model outputs manually is time-consuming, error-prone, and a major bottleneck for large datasets. For some understudied taxa (e.g., fish), most work is still manual	Use BirdNET Review, Raven, Triton, DetEdit, Kaleidoscope; validate subsets of detections; consensus annotation; pre-validated datasets; active learning and filtering.	Semi-automated validation with AI-assisted review, confidence scoring, consensus tools; open repositories of annotated datasets; collaborative cloud platforms.
Handling, Storing, and Sharing Data	39	PAM generates massive datasets that are difficult to store, back up, or share; inconsistent file formats and metadata hinder reuse.	External drives, SSDs, NAS, fragmented cloud (Box, AWS, Arbimon, WildTrax); compress files; adopt metadata standards appropriate for acoustic data; FTP servers; ship drives in low-bandwidth areas.	Centralised, open-access repositories with standardised metadata; affordable, renewable-powered cloud storage; regional data nodes; free storage for conservation projects.
Standardisation and Comparability	35	Lack of agreed standards for metrics, recording settings, metadata, and reporting limits reproducibility and ecological synthesis.	Precise reporting of study design and settings; core metrics for comparability; use acoustic/ISO standards; workshops and benchmarking initiatives.	Internationally agreed standards (ISO-level) for recording, metrics, and reporting; calibration protocols; open-access handbooks; global consortia to drive adoption.
Computational Barriers	24	Running detection/classification at scale requires computing resources unavailable to many, especially in the Global South.	Use university clusters, Google Cloud, AWS, Arbimon, EcoSoundWeb; subsample/compress data; parallel R/Python workflows; fine-tune models; optimised planning of data analyses.	Scalable, cloud-ready PAM platforms with built-in optimisation, parallelisation, and equity of access; distributed computing hubs; real-time, field-ready processing.
Cost and Licensing	15	High licensing fees and proprietary restrictions block access, especially in resource-limited regions; open tools exist but are fragmented.	Free/open-source tools (BirdNET, Arbimon free tier, PAMGuard, RavenLite, R/Python); discounted licenses; collaborative license sharing; GitHub workflows.	Free, open-source PAM platforms sustainably maintained; publicly funded support; tiered systems where companies pay and academics access free; modular, well-maintained open tools.
Visualisation and Reporting Tools	6	Limited tools exist to generate clear visualisations, summaries, or integrated reports, complicating communication with stakeholders.	Use Raven, Audacity, PAMGuard, seewave, warbleR, monitoR; custom R/Python scripts; Power BI, Shiny dashboards; Arbimon and WildTrax for partial integration.	Integrated platforms with automated spectrograms, summaries, and reports; seamless integration of environmental/camera trap data; open, modular systems akin to Arbimon + Raven + Shiny + QGIS + eBird combined.

Labs, Teledyne Reson, MTE Instruments, or SwiftOne (2–3 respondents each). A few participants reported alternative systems, including SNAP Recorders (Loggerhead Instruments), MARU and Rockhopper recorders (K. Lisa Yang Center for Conservation Bioacoustics), Cetacean Research Technology, and SonoVault recorders (Fig. 1D).

3.1. Bottlenecks for analysing PAM data

Nine bottlenecks emerged from our analysis (see Table 2 for a summary). *AI-based species identification* emerged as the highest priority challenge, receiving the highest total score (105), reflecting widespread concern about the limited accuracy, transparency, and cross-taxon applicability of current AI classification models. The second most prominent theme, *workflow fragmentation* (78), underscored frustration with disconnected tools, and the need for integrated analysis pipelines. The lack of *user-friendly software* ranked third (65), with many respondents emphasising steep learning curves and limited accessibility of current platforms.

Other recurring themes included *manual validation* (42), *data handling and sharing* (39), and *standardisation and comparability* (35), all of which point to barriers that limit efficiency and reproducibility. Lower-ranked but still notable themes included *computational barriers* (24), *cost and licensing* (15), and *visualisation and reporting tools* (6). Despite variation in scores, all themes included responses from multiple

experts, indicating a broad, interrelated set of challenges currently limiting the scalability and adoption of PAM. To support practical responses to these challenges, a set of Supplementary Guides was developed alongside this synthesis, each targeting specific bottlenecks with step-by-step approaches and examples (see Box 1 and Supplementary Guides 1–8).

3.2. AI species identification (total score: 105 – highest priority)

Improving how we use deep learning models and AI more broadly to accurately and efficiently identify species and sound types was voted by the respondent group as the most urgent challenge in PAM. Across ecosystems, PAM is hampered by high error rates in automated species identification (Barré et al., 2019; Metcalf et al., 2022). The performance of AI classifiers varies considerably across taxa, regions, recorders, and recording conditions (Funosas et al., 2026), especially in the presence of dialect variation, intra-specific variability, or species with similar calls, as well as background noise in recordings (Gibb et al., 2019; Hall et al., 2025). Therefore, there is a need for robust and standardised validation procedures to avoid misinterpretation of outputs. Another recurring issue identified in the survey is the lack of open-access annotated reference datasets for training or benchmarking models, as annotation is a time-consuming process that requires significant expertise in the studied species. In the absence of open, standardised calibration datasets

and geographically diverse training data, even classifiers that perform well under benchmark conditions can fail unpredictably when applied to new species, regions, or recording setups, limiting their reliability and transferability in real-world PAM applications (Funosas et al., 2026; Wood and Kahl, 2024; Ziegenhorn et al., 2023).

3.3. Workflow fragmentation (total score: 78)

Respondents highlighted that workflows regarding PAM processing remain fragmented. Navigating from data storage to acoustic analyses, model validation, statistical analyses and data reporting often requires using several different tools, which often lack compatibility. For example, the detector output from one software may not integrate seamlessly with manual annotation platforms or downstream statistical packages. This creates inefficiencies, increases the risk of data loss or misinterpretation, and makes it harder to scale up analyses across large datasets or multiple projects.

3.4. User-friendly software (total score: 65)

The respondents identified that a major barrier to wider use and innovation in PAM is the technical complexity of the tools. Many researchers and practitioners in the fields of ecology or applied conservation are not professional programmers, which often reduces the potential of citizen science in PAM surveys. Although several current platforms already provide graphical user interfaces (GUIs; see the next section), a large fraction of tools available for PAM processing still do not offer such advantages and require advanced coding skills or familiarity with programming environments such as R, Matlab or Python (see Hanf-Dressler et al., 2026 for an overview of available bioacoustics software).

3.5. Manual validation (total score: 42)

Manual review of model predictions is essential for ensuring reliability and ecological validity of automated outputs. However, respondents highlighted a lack of software tools that support efficient, structured, and transparent validation, including built-in quality controls, prioritisation of detections (e.g., by confidence scores), or clustering of acoustically similar calls to streamline review. As a result, current workflows often require users to switch between multiple, poorly integrated tools such as detection software, spectrogram viewers, and spreadsheets, increasing both time costs and the risk of error. These findings highlight the need for integrated validation environments that preserve the critical role of expert judgement while making manual review faster, more consistent, and more collaborative.

3.6. Handling, storing, and sharing data (total score: 39)

Data management challenges are growing as more recorders are deployed over longer periods. Some teams now work with petabytes of data, yet storage infrastructure, backup solutions, sound archive infrastructure, and metadata management have not kept pace. Although most projects use .WAV, file formats are often inconsistent across devices or projects, and few tools offer built-in metadata validation or compatibility with online biodiversity repositories like iNaturalist, Xeno-Canto or GBIF. Sharing data across institutions, sound archives, or even among team members can be difficult due to access restrictions, lack of cloud integration, or poor searchability within archives. There is a lack of standard protocols for organising folders, naming files, and synchronising annotations, which greatly reduces interoperability among projects. These issues reduce reproducibility, increase overhead, and make it hard to contribute to broader meta-analyses or cumulative research efforts.

3.7. Standardisation and comparability (total score: 35)

Despite the diversity of tools and platforms for processing PAM data (Hanf-Dressler et al., 2026), there are few guidelines and standards about what constitutes best practice. This hinders the ability to compare results across projects or build general knowledge. Metrics such as signal-to-noise ratio, detection thresholds, or classification accuracy are often reported inconsistently or omitted entirely, and few tools include calibration routines or reference levels to enable instrument comparability. Major differences also exist between terrestrial and aquatic research, reflecting the distinct characteristics and monitoring requirements of these environments. In addition, the required metadata fields and their structures differ widely across software tools, and users commonly struggle to merge datasets without extensive cleaning. These findings highlight the need for community-driven standards for data formats, analysis parameters, and reporting structures, perhaps with minimal but enforceable core requirements to ensure interoperability and data longevity.

3.8. Computational barriers (total score: 24)

Although computational resources have improved, many PAM users still encounter bottlenecks, especially when processing large amounts of audio or using custom deep-learning models. Training or fine-tuning models often requires GPUs or cloud infrastructure that may be unavailable or expensive. Even seemingly basic steps, such as loading a spectrogram or batch processing, can become slow on older systems or when working remotely. These delays are particularly acute in projects aiming for real-time or near-real-time analysis. Without better tools for parallel processing, optimised storage formats, or lightweight review interfaces, PAM is unlikely to achieve the level of scalability required for large-scale biodiversity monitoring, at least for certain groups and regions.

3.9. Cost and licensing (total score: 15)

Cost and licensing constraints remain a significant barrier to the uptake and scalability of PAM workflows, particularly for researchers with limited funding or institutional support. Many widely used PAM and bioacoustics platforms rely on proprietary licenses, with annual fees typically ranging from hundreds to several thousand USD per user or project, depending on functionality and data volume, which can restrict access to advanced features or limit team-wide use. In addition, cloud-based processing introduces recurring costs for storage, computing, and data transfer, which can quickly accumulate to hundreds or thousands of USD per year for projects managing large acoustic libraries or supporting collaborative access. Together, these costs can force reliance on outdated or poorly maintained free tools. These findings suggest that greater investment in open-source software, together with transparent licensing and infrastructure costs, would improve equitable access to PAM tools and support reproducible, globally inclusive methodological innovation.

3.10. Visualisation and reporting tools (total score: 6 – lowest priority)

Relatively few respondents identified visualisation and reporting as a major pain point, resulting in the lowest total score among the nine themes. Nevertheless, those who did raise this issue emphasised the challenge of translating PAM outputs into clear, actionable insights for end users. Many tools lack effective visualisation options, such as displaying presence/absence maps, species trends, or annotated spectrograms for review. Reporting functionalities are also limited, requiring manual compilation of figures or metrics for funders, managers, or collaborators. Such reporting should always include a description of the parameters used for recording and spectrogram visualisation (i.e. FFT size, overlap, frequency resolution) to ensure reproducibility across

studies, an aspect emphasised by several respondents. While this category had the lowest priority, its identification as a bottleneck highlights its importance in supporting uptake and outreach beyond the research community.

4. Current strategies for bottlenecks

The strategies presented in this section are derived from the second stage of the consultation, which combined responses from the follow-up survey with iterative discussions and consensus-building among the participating co-authors. Accordingly, we use the term “participants” rather than “respondents” throughout this section.

Building on the bottlenecks identified during the initial expert consultation, we compiled and refined a set of strategies to address each challenge through an iterative synthesis and validation process (see Table 2 for a summary), involving 24 of the original 30 respondents as participants. The resulting strategies reflect practices already in use or widely recognised by PAM experts within the respondent cohort. Each strategy is complemented, where applicable, by a corresponding Supplementary Guide that translates these practices into reproducible workflows and practical instructions. The following section consolidates existing approaches informed by expert experience, rather than an independent ranking or quantitative assessment. The strategies are organised by bottleneck to highlight how current practice is distributed across key constraints in PAM workflows.

4.1. AI species identification

A widely endorsed approach by the participants for improving AI-based species identification in real-world PAM workflows involves customising existing foundation models or pretrained architectures (e.g., BirdNET and Perch) to new taxa or acoustic contexts using transfer learning, either within or across domains (Bell et al., 2026; Ghani et al., 2023; Márquez-Rodríguez et al., 2026; Williams et al., 2025). To support this process in practice, Supplementary Guide 1 provides a step-by-step workflow for adapting BirdNET models to non-avian species through transfer learning. Participants viewed this strategy as particularly important for addressing persistent gaps in taxonomic and regional coverage while leveraging the robustness of existing models.

Several participants also highlighted that many PAM applications operate with limited or completely absent labelled training data. To address this issue, Supplementary Guide 2 outlines practical workflows based on embeddings and clustering to develop acoustic classifiers with little or no annotated data. Participants noted that such approaches may be especially useful for understudied taxa and regions where expert-labelled datasets remain scarce.

To further reduce limitations associated with small training datasets, participants frequently recommended data augmentation approaches to artificially expand acoustic training libraries. Supplementary Guide 3 summarises practical augmentation workflows currently used in PAM, including noise injection, pitch shifting, time stretching, and synthetic variation generation.

Participants consistently emphasised that automated detection alone is insufficient for reliable ecological inference, underscoring the need for workflows that combine AI-based classification with targeted manual validation. Supplementary Guide 4 focuses specifically on integrating classifier uncertainty and validation procedures into ecological analyses to reduce or better quantify the risk of incorrect inferences. Suggested strategies included prioritising subsets of detections for expert review (Chronister et al., 2025; Katsis et al., 2025), applying biologically informed thresholds and statistical filters (Wood and Peery, 2022), using staged detection pipelines to isolate target vocalisations prior to species classification (Márquez-Rodríguez et al., 2025), or ensemble approaches that combine outputs from multiple models to reduce error rates (Pérez-Granados et al., 2024).

Collaboration emerged as a cross-cutting solution throughout this

category. Participants advocated pooling annotated datasets across projects and regions, engaging citizen science to expand validation capacity or refine existing models, and sharing open code and workflows to support community-driven improvements. These needs were seen as particularly acute in aquatic environments, where most recorded sounds remain unidentified, motivating collaborative initiatives such as Fish-Sounds (Looby et al., 2023) and the Global Library of Underwater Biological Sounds (GLUBS; Parsons et al., 2023).

4.2. Workflow fragmentation

Participants highlighted that the main way to cope with workflow fragmentation today is by manually stitching together disconnected tools while maintaining consistency through careful file organisation, documentation, and coding. Many rely on R and Python pipelines (e.g., warbleR, vegan, monitoR, or seewave for R, and scikit-maad for Python) to integrate outputs from multiple programs, while others use modular platforms such as Arbimon, BirdNET-Analyzer, PAMGuard, Raven, or EcoSoundWeb to complete as many workflow steps as possible within a single environment.

To support these integration strategies in practice, Supplementary Guide 5 provides an example of a reproducible multi-tool workflow in R, illustrating how outputs from different PAM software packages can be standardised, merged, and analysed within a single pipeline.

Participants also emphasised the importance of standardised file formats (e.g., CSV structures and metadata schemas), relational databases, and dashboards for centralised visualisation and reporting. Several participants described using custom templates and Standard Operating Procedures (SOPs) to improve reproducibility across teams, while others collaborated directly with software developers to encourage interoperability among platforms. Despite these strategies, participants acknowledged that fragmented workflows still require substantial manual intervention and remain time-consuming to maintain.

4.3. User-friendly software

Researchers often rely on GUI-based tools such as BirdNET-Analyzer, Kaleidoscope Pro, Raven Pro, Arbimon, PAMGuard, Triton, and Wild-Trax. However, participants noted that these platforms still present limitations in taxonomic coverage, transparency, interoperability, or accessibility due to licensing costs. A common strategy for reducing these barriers is to combine GUI-based tools with tutorials, training workshops, and shared annotated R/Python scripts (e.g., R Markdown and Jupyter notebooks) that help non-programmers navigate more complex workflows.

Several participants also described developing custom Shiny Apps or simplified coding interfaces to make PAM analyses more accessible to users with limited programming experience. Supplementary Guide 6 provides a practical example of how GUI-based interfaces can be developed to bridge the gap between complex analytical workflows and non-programming users. Others highlighted collaborations with computer scientists as an effective way to gain access to more advanced analytical pipelines while maintaining usability for broader research teams.

4.4. Manual validation

To cope with the heavy burden of manual validation, participants emphasised combining automation with selective human oversight. Many reported using tools such as BirdNET-Analyzer, Raven Pro, Triton, DetEdit, Arbimon, and Kaleidoscope Pro, often integrated with custom scripts to streamline spot-checking and label editing. Rather than exhaustively validating every detection, a recurring strategy was to prioritise uncertain or low-confidence outputs, or to incorporate detection uncertainty directly into downstream analyses using statistical

approaches such as occupancy models.

Supplementary Guide 4 formalises these strategies into a reproducible workflow for incorporating classifier uncertainty into ecological inference. The guide illustrates practical approaches for reducing validation effort while maintaining analytical reliability, including selective review of detections, biologically informed filtering, and error-aware modelling approaches. Participants also recommended clear annotation guidelines, distributing validation effort across multiple trained users, and using consensus-based approaches to reduce subjectivity.

Several participants further highlighted the importance of open-access curated datasets for benchmarking models and reducing repetitive validation work (Pérez-Granados et al., 2026). Active learning and filtering strategies, such as prioritising species expected at a location or initially reviewing high-probability detections, were commonly used to reduce effort without substantially compromising reliability. Citizen science initiatives, including the Forest Listeners project and Google Arts & Culture, were also identified as emerging approaches for expanding validation capacity.

4.5. Handling, storing, and sharing data

Participants described a range of stop-gap solutions for managing and sharing large acoustic datasets. Many rely on combinations of external hard drives, SSDs, NAS systems, fragmented cloud storage platforms (e.g., Box, Google Drive, Amazon Web Services, Arbimon, WildTrax), and repositories such as Zenodo to store and transfer data. Several participants reported using compressed open formats such as FLAC to reduce storage requirements, although uncompressed formats (e.g., .WAV) remain the most common standard for archival storage and analysis.

Participants consistently emphasised that improving interoperability depends on adopting standardised metadata structures and file-naming conventions, including frameworks such as Darwin Core (Wieczorek et al., 2012), GUANO (Reichert et al., 2018) or Tethys (Roch et al., 2013). Supplementary Guide 7 presents common practices for acoustic data management, explaining how metadata standards, folder structures, and naming conventions can be implemented to improve data organisation, interoperability, and long-term reproducibility.

Despite these approaches, participants noted that data management strategies remain fragmented and strongly dependent on local infrastructure and resources, with particular challenges in the Global South where storage, backup, and cloud access capacity may be limited.

4.6. Standardisation and comparability

Participants highlighted that the lack of standardisation remains a persistent barrier to comparability across PAM studies but also identified several practical steps to improve consistency. Many stressed the importance of detailed reporting of study design, hardware configurations, preprocessing settings, and software parameters to support reproducibility and cross-study comparisons, following initiatives such as MANTA ("Making Ambient Noise Trends Accessible"; Miksis-Olds et al., 2021). Others recommended adopting core sets of metrics that can be consistently reported across projects while retaining flexibility for study-specific objectives.

Participants frequently pointed to existing metadata standards, including Darwin Core, ISO initiatives, and Acoustical Society of America guidelines, as a starting point for improving interoperability. Supplementary Guide 7 provides a practical workflow for implementing these standards in PAM data management, including metadata structures, file naming conventions, and documentation practices designed to improve reproducibility and comparability across studies.

Several participants also noted that standardisation is complicated by differences among taxa, ecosystems, recording systems, and regional requirements. As a result, collaborative approaches such as workshops, international networks, and cross-project benchmarking exercises were

identified as important mechanisms for promoting transparency, alignment, and gradual convergence toward shared best practices (Wall et al., 2025).

4.7. Computational barriers

Participants described a range of pragmatic and collaborative strategies to overcome computational barriers in PAM analyses. The community commonly rely on university high-performance computing clusters, public servers, or cloud-based platforms (e.g. Google Cloud, AWS, Arbimon, EcoSoundWeb), while others partner with colleagues or institutions that have access to advanced computing infrastructure. To reduce computational demands, participants reported optimising workflows through data subsampling, file compression, and the use of foundation models such as BirdNET and Perch, including fine-tuning existing models for specific applications. Several respondents emphasised that effective PAM begins with a realistic survey design, where the volume of data collected is matched to the computational resources available for storage, processing, and analysis. Participants also recommended integrating parallel processing and lightweight R or Python pipelines to maximise efficiency on standard desktop or laptop computers. Beyond improving accessibility and reducing computational costs, efficient workflows may also reduce reliance on energy-intensive computing infrastructure, including data centres, thereby lowering the environmental footprint of large-scale PAM analyses.

4.8. Cost and licensing

Participants emphasised that many effective free or open-source tools are already available for PAM workflows, including BirdNET, Arbimon (free tier), Perch, PAMGuard, PamGUIDE, MANTA, RavenLite, and a wide range of R and Python packages. Where proprietary tools are still commonly used (e.g., Kaleidoscope Pro, Raven Pro, Matlab), researchers often rely on free versions, discounted academic licenses, institutional access, or region-specific exemptions such as Raven Pro licenses for researchers in the Global South. The PAM software landscape also continues to evolve rapidly, with some platforms moving toward commercial subscription models (e.g., Arbimon), while others are expanding free access or making tools open-source (e.g., Raven Workbench).

Many participants also described building reproducible open-source workflows using R and Python, developing custom scripts, and sharing tools through GitHub, Zenodo, and other public repositories. Supplementary Guide 8 provides a practical framework for developing transparent, reproducible, and shareable PAM analysis pipelines, including recommendations for version control, code annotation, workflow documentation, and reproducible data processing practices.

Collaborative approaches were also identified as important mechanisms for reducing costs and improving accessibility. These included negotiating shared licenses across research teams, forming collaborative networks to apply for funding, and leveraging institutional infrastructure to support computationally intensive workflows.

4.9. Visualisation and reporting tools

To overcome gaps in visualisation and reporting, many participants reported combining multiple tools such as Audacity, Raven, BirdNET-Analyzer GUI, PAMGuard, and Triton with custom R and Python scripts using open-source packages including seewave, warbleR, and monitoR. Participants noted that interactive dashboards built with R Shiny or business intelligence platforms such as Power BI are increasingly being used to create shareable and user-friendly summaries for collaborators, managers, and decision-makers.

Supplementary Guide 6 demonstrates how GUI-based interfaces and interactive dashboards can be developed to improve accessibility, communication, and interpretation of PAM outputs, particularly for

users with limited programming experience. Several participants highlighted these approaches as important for bridging the gap between technical analyses and operational decision-making.

Integrating PAM outputs with environmental metadata, eDNA, or camera trap datasets remains challenging and often requires bespoke coding solutions (Lombardo et al., 2025). While collaborative platforms such as ArbiMon and WildTrax provide partial solutions for linking PAM with other ecological datasets, participants noted that workflow fragmentation and interoperability limitations remain major barriers to fully integrated reporting systems.

5. Emerging opportunities and future directions

In addition to currently implemented strategies, participants identified a range of emerging opportunities to address the major bottlenecks in PAM workflows (see Table 2 for a summary). These opportunities were developed through the later stages of the consultation process and reflect forward-looking perspectives shaped by iterative discussion and refinement among participants. In several cases, these forward-looking directions build directly on the practical workflows outlined in the Supplementary Guides, which provide current implementations or partial solutions to these longer-term challenges.

Unlike the outputs of the initial expert consultation, these proposals are not derived from independent responses but represent community-informed directions that may guide future methodological development. As such, the level of agreement around these opportunities reflects convergence within the participating cohort, rather than independent replication across the broader expert community. They should be interpreted as plausible and aspirational pathways, whose implementation may depend on factors such as technical capacity, infrastructure, and resource availability. As in the previous section, opportunities are organised by bottleneck to maintain consistency with the structure of identified challenges.

5.1. AI species identification

Participants in the follow-up survey emphasised the need for globally diverse, open-access, and reliable annotated datasets, as well as generalisable AI models capable of handling a wide range of taxa, geographies, and recording conditions. Several envisioned a collaborative platform that would function as both a model- and dataset-sharing hub, enabling researchers to upload, adapt, and retrain models in a streamlined way. The development of explainable AI (tools that make model decisions interpretable) was highlighted as critical for building user trust. Experts also called for better built-in uncertainty metrics that go beyond raw confidence scores, including clearer information on how well each species is represented in training data, how training data are distributed across a species' range, and how likely model performance is to vary among regions or recording conditions. Separately, participants emphasised the need for user-friendly interfaces that would allow ecologists without coding skills to assess, validate and adapt classifier outputs. Some stressed the value of foundational AI models, akin to large language models, that could be fine-tuned for specific ecological contexts or taxa. Others saw the future in standardised protocols for training and validation, ensuring comparability across studies. Although fully generalisable “all-species” classifiers are not yet available, participants saw clear potential in rapidly developing, scalable frameworks that integrate local adaptation, ensemble modelling and transparent reporting, allowing AI species identification to mature into a robust and reliable tool for global biodiversity monitoring.

5.2. Workflow fragmentation

The vision for an ideal solution was clear: a fully integrated, interoperable, and modular PAM platform that seamlessly handles annotation, detection, classification, validation, metadata management,

storage, and reporting within a single workflow. Some envisioned a “one-stop shop” solution for acoustics, analogous to geospatial platforms such as ArcGIS or QGIS, where all modules interconnect but can also be updated independently as methods evolve. The development of a cloud-based infrastructure that offers scalability for large datasets, automated documentation of workflows, and real-time collaboration across teams would facilitate the adoption of universal standards for annotation formats, acoustic features, and metadata while remaining flexible enough for local adaptation. Importantly, participants emphasised that the future platform must be user-friendly and either open source or have commercial licensing models reserved exclusively for corporate use. Since completing the survey, development of a free, modular PAM platform has begun within the Raven environment. However, key aspects remain absent or unclear, including the support for multi-user collaboration, the ability to search for similarity among embeddings, and integrated data storage capabilities.

5.3. User-friendly software

Looking ahead, participants consistently envisioned a more inclusive PAM landscape where user-friendly software is the norm. The ideal solutions would be open-access, GUI-based platforms capable of guiding users through every step of the workflow without requiring coding: detection, classification, validation, and reporting. Such platforms should be modular, intuitive, interoperable, and adaptable across taxa and environments, with consistent terminology, integrated tutorials, and context-sensitive help. Others suggested that collaboration with big tech companies or startups could accelerate the development of robust, affordable tools, potentially integrating co-pilot features to support occasional coding needs. Ultimately, participants hope for software ecosystems that shift the focus away from technical hurdles and back to ecological interpretation and conservation impact.

5.4. Manual validation

Participants in the follow-up survey envisioned semi-automated, AI-assisted validation systems that minimise human workload while maintaining transparency and trust in the validation process. Desired features include intuitive review interfaces, built-in confidence scoring, consensus tools, and error metrics that help prioritise ambiguous detections. Consensus emerged for centralised, open-access repositories of annotated datasets that could serve as benchmarks, training resources, and validation references across taxa and regions. Many also expressed interests in cloud-based platforms with integrated detection, validation, and statistical tools, enabling collaborative review and large-scale consistency. In an ideal scenario, detection models would become accurate enough that manual validation is rarely required, with human review reserved primarily for quality control of rare or unknown sound types; however, this outcome is unlikely to be realised in the near term. As such, agile interfaces that combine automated detection, guided human annotation, and continuous model improvement were viewed as the most promising path forward.

5.5. Handling, storing, and sharing data

Although depositing sound files in well-established sound archives is still a recommended and incentivized practice (Dena et al., 2024; Mendoza-Henao et al., 2021; Toledo et al., 2015), participants widely agreed on the need for a centralised, open-access repository for PAM data, ideally with standardised metadata requirements and globally agreed file formats. Many envisioned a cloud-based system (affordable, scalable, and user-friendly) that would automate backups, metadata capture, provenance tracking, and collaborative sharing. Some saw potential in building a global network of regional data nodes to distribute storage costs and ensure long-term preservation. In parallel, participants called for stronger investment in high-biodiversity regions

and free storage for conservation-focused projects, supported by governments, institutions, or large technology providers. A more realistic near-term goal may be improved interoperability between existing archives and analysis platforms, enabling data to be stored, discovered, and reused without being lost at the end of individual projects. This could be advanced through practical connections between existing systems, such as tools that export PAM outputs in archive-ready formats, retain links between recordings and derived annotations, and allow validated detections, metadata, and provenance information to move more easily between repositories and analysis platforms.

5.6. Standardisation and comparability

Participants in the follow-up survey envisioned the creation of ISO-level guidelines or open-access handbooks with clear, taxa-specific recommendations, supported by calibration protocols and benchmarking datasets. Ensuring dedicated funding and global consortia to drive standardisation efforts and aligning ecoacoustics with existing frameworks (e.g., GOOS (Tyack et al., 2023), IQOE (Tyack et al., 2015), TG Noise (Dekeling et al., 2014)) will contribute to the required standardisation. However, we recognise that such coordination is unlikely to emerge quickly without dedicated funding, institutional support, and sustained community leadership, as many of these tasks are difficult to deliver through voluntary effort alone. There was broad consensus that an open, published international standard, broken down by taxa, environments, or regions, would greatly improve reproducibility and ecological synthesis, enabling PAM outputs to be meaningfully compared across scales.

5.7. Computational barriers

Looking ahead, participants envisioned user-friendly, cloud-based platforms with equitable access to computational resources as the long-term goal for supporting PAM workflows at scale. Ideally, these platforms would provide free or low-cost access, particularly for researchers and conservation groups in the Global South, while integrating parallel processing, containerisation, and built-in optimisation to efficiently handle very large datasets. Some participants also pointed to the potential of shared or distributed computing approaches, in which idle processing capacity could be pooled across institutions, drawing inspiration from citizen science models such as SETI@home (Anderson et al., 2002). However, others noted that this approach may be difficult to implement in practice for PAM workflows. Compared to cloud-based or institutional computing, distributed systems introduce challenges related to data transfer, hardware heterogeneity, and job management, which can substantially increase engineering overhead. As a result, such approaches are currently better viewed as exploratory or aspirational, rather than near-term solutions.

Existing solutions such as Arbimon already incorporate several elements of this broader vision. However, recent shifts toward tiered pricing models, where free access is limited to lower usage levels, together with limited flexibility in integrating external classifiers across platforms, have discouraged some users from fully adopting these systems. Overall, while elements of this vision are already emerging, the development of fully integrated, scalable, and accessible PAM platforms remains an ongoing challenge.

5.8. Cost and licensing

Participants in the follow-up survey envision a future where PAM processing tools are widely accessible, with strong open-source components that reduce barriers across research communities. While some expressed a preference for fully free systems, this was generally recognised as aspirational, given the ongoing costs of development, maintenance, documentation, and user support.

Participants identified several sustainability pathways. Public

funding (e.g., research grants or national infrastructure programs) can support initial development, but long-term maintenance is often underfunded. Philanthropic support may help in specific cases but is unlikely to provide stable coverage. More durable approaches may involve hybrid models, including institutional support, community-led development, service-based funding (e.g., paid hosting or storage), or tiered access where commercial users contribute while academic and non-profit users retain free or low-cost access.

Participants also pointed to parallels with geospatial infrastructures such as Google Earth Engine, which provide free or low-cost access to large-scale data storage and computation. However, translating this model to PAM is not straightforward. Acoustic datasets are often large, continuous, and less standardised, and workflows require custom pre-processing, model training, and validation. As a result, while such platforms may be feasible in principle, they would require substantial coordination, standardisation, and sustained funding. In the near term, hybrid models that combine open-source tools with cloud or institutional infrastructure are more realistic than fully integrated, universally free systems.

5.9. Visualisation and reporting tools

Looking ahead, the vision converges on the development of integrated and user-friendly platforms capable of combining metadata integration, detection, validation, visualisation, and reporting in one streamlined workflow (Rountree et al., 2020). Participants imagined systems that could automatically generate interactive spectrograms, diel or seasonal summaries of the predictions validated, and stakeholder-ready reports without requiring extensive coding in R or Python. Such platforms should allow seamless incorporation of environmental variables, GPS, eDNA, and camera trap data in a spatially explicit way, enabling ecological inference such as occupancy or density models. Automated quality checks for issues like clipping or internal noise were seen as valuable additions to accelerate early-stage validation. Importantly, these systems should be open-source, modular, and reproducible, evolving alongside community needs. The overarching ideal resembles a unified ecosystem (something akin to combining Arbimon, Raven, Shiny dashboards, QGIS, and eBird) capable of serving both researchers seeking detailed analysis and decision-makers requiring accessible summaries.

6. Conclusions and future directions

We conducted a structured, community-informed consultation with a subset of PAM experts to highlight current challenges faced in PAM workflows, along with current strategies, emerging directions and future priorities. While experts identified nine bottlenecks, a recurring message was that solutions already exist, in part, for most of the challenges. To support their implementation, we provide eight Supplementary Guides that translate currently available strategies into practical workflows that users can directly adopt or adapt. Therefore, the problem is less about a lack of innovation than about fragmentation, duplication, interoperability issues, and uneven access. Reinventing the wheel remains common, but this approach is ultimately counterproductive. Progress will depend on building bridges among existing tools, datasets, and communities, rather than expecting that a single lab or project can develop the definitive solution in isolation.

A less explicit bottleneck, which emerged indirectly from survey responses, was a gap not only between the tools practitioners need and the tools available, but also between available tools and awareness of them. Many participants called for broader species coverage in classifiers, and all-in-one graphical interfaces that support the full PAM workflow. Since the first survey was distributed, there have already been substantial developments in these areas. For instance, recent BirdNET Analyzer releases have expanded GUI-supported workflows for analysis, training, validation, embeddings and evaluation, while also adding

Perch v2 as an alternative classifier. Perch v2 itself offers classification for almost 15,000 species, including birds, mammals, amphibians and insects. In a rapidly developing field, no individual practitioner can be expected to track every new platform, classifier, package, or version update. This reinforces the need for practical guidance and more coordinated knowledge-sharing mechanisms, potentially through professional working groups or resource hubs that disseminate regular updates through a range of media platforms and channels to help practitioners keep pace with new tools, functions, and limitations.

A central theme across all categories is the need for interoperability. Whether in AI model development, metadata standards, or visualisation platforms, participants stressed that consistent formats and modular design would allow tools to be combined flexibly, reducing inefficiency and enabling broader collaboration. This approach requires not only technical solutions but also governance structures (international standards bodies, consortia, or community-led working groups) that can coordinate efforts and ensure adoption across taxa, geographies, and user communities. Lessons from other fields, such as genomics and remote sensing, demonstrate that such coordination is possible and can dramatically accelerate synthesis.

These challenges and opportunities have direct implications for policy and operational monitoring systems. Monitoring costs, scalability, and verification remain key constraints for emerging biodiversity policies, including biodiversity credit schemes and large-scale conservation programs (Bell and Malerba, 2025; Ford et al., 2024; Kim et al., 2025). In this context, PAM offers a pathway to increase temporal coverage and detection rates while reducing costs, particularly for vocalising taxa. However, the current limitations in PAM workflows discussed here, such as fragmented tools, limited standardisation, and uncertainty in classifier performance, constrain its use in regulatory and decision-making contexts. Addressing these barriers is essential to enable reliable, repeatable, and scalable monitoring programs that can support verification, accountability, and long-term deployment in policy-relevant applications.

Equity also emerged as a cross-cutting priority. While well-resourced institutions in the Global North may overcome computational and licensing barriers with local infrastructure, participants reminded us that many high-biodiversity regions remain under-resourced. Without targeted investment, free or subsidised access to tools, and tiered support models, the global PAM community risks exacerbating inequalities in biodiversity monitoring. Ensuring that open-access repositories, user-friendly interfaces, cloud infrastructure, and training opportunities are available to researchers and practitioners worldwide is therefore essential to delivering on PAM's promise as a truly global approach to conservation.

Although we adopted a systematic approach to expert selection, the perspectives reported here reflect the experience of a subset of the global PAM community and may not capture the full diversity of approaches and priorities in the field. In addition, because introductory questions about PAM hardware and software preceded the open-ended bottleneck questions, the questionnaire may have indirectly encouraged participants to focus on the technical aspects of PAM workflows rather than on factors that influence how outputs are translated into decision-making. Therefore, our findings should be interpreted with caution. For example, “Visualization and Reporting Tools” was the only category directly addressing how PAM outputs are translated into decision-making, and although recognised among the top bottlenecks, it received the lowest priority score. This pattern may reflect several factors, including the stronger emphasis of participants on technical challenges (e.g., data processing and model performance), the framing of the questionnaire, and the fact that visualisation and reporting are generally supported by established, widely adopted software (e.g., R, Python, Excel) rather than requiring specialised PAM-specific tools.

Looking forward, the most constructive path lies in developing a

shared roadmap: a modular, open, and community-driven ecosystem for PAM. This ecosystem should integrate data storage, detection, classification, validation, and reporting in a transparent and user-friendly way, while maintaining flexibility for local adaptation and innovation. Achieving this vision will require collaboration across disciplines, bringing together ecologists, computer scientists, software developers, funders, and policymakers, and dedicated investment in infrastructure and capacity-building. If the field can avoid working in isolation, embrace shared standards, and channel collective effort into interoperable solutions, PAM has the potential to mature into a cornerstone of biodiversity monitoring, delivering actionable insights at the scales needed to confront global ecological change.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used OpenAI ChatGPT (5.5) to improve readability and proofread the document. The authors reviewed and edited the output as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecoinf.2026.103971>.

Data availability

The data and analyses of the two surveys supporting the results of this study are in a public repository ([10.6084/m9.figshare.32496705](https://doi.org/10.6084/m9.figshare.32496705)).

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