

1. Abstract

Passive acoustic monitoring (PAM) enables non-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 create fragmented and complex analytical workflows. To identify the key barriers and opportunities shaping the implementation of PAM surveys, we conducted a structured expert solicitation involving 30 international practitioners working across terrestrial and aquatic ecosystems. Experts identified and ranked their most critical pain points 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. Participants also proposed 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.

Keywords:

passive acoustic monitoring, bioacoustics, workflow optimisation, software bottlenecks, artificial intelligence, scalable ecological monitoring, data management

2. 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 scale is critical for identifying and tracking these changes, implementing conservation actions, and assessing the effectiveness of restoration efforts (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 (Gibb et al. 2019, Darras et al. 2025). 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 it generates (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 1,000 per terrestrial unit and USD 5,000 per aquatic unit (REF here). 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). This hardware transition enables unprecedented data collection across large spatial and temporal scales (Sugai et al. 2019, Stowell and Sueur 2020, Hoefer et al. 2023). 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. While major progress has been made in automated detection and classification, particularly through the rise of deep-learning and foundation bioacoustic models (Kahl et al. 2021, Hamer et al. 2023, van Merriënboer et al. 2025), these advances have not been matched by equivalent progress in the broader software ecosystems required to manage, analyse, and interpret large PAM datasets. 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.

In this study, we employed a structured expert consultation to identify the key technical and practical barriers limiting the scalability, accessibility, and reproducibility of PAM analyses for biodiversity monitoring. Open-ended responses were scored and ranked to prioritise the pain points 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. We then summarise expert-endorsed strategies currently used to mitigate these barriers, highlighting practical tools and approaches already available. We also 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. Together, these insights provide a roadmap for turning PAM into a more accessible, interoperable, and impactful tool for biodiversity monitoring and conservation.

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. *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 5. *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 6. *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 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.

3. Material and Methods

3.1. Expert Identification

We compiled an initial list of PAM specialists by selecting the top 100 most-cited researchers in the field (each with a minimum of five peer-reviewed publications on this topic). Citation data were extracted from the Web of Science platform on the 4th of June 2025. This list was subsequently expanded through purposive and snowball sampling, incorporating additional experts identified through collaborator recommendations and their recognised roles in prominent PAM projects, monitoring programs, and software development initiatives. The combined approach ensured representation across sectors, geographic regions, ecosystem types, and taxonomic expertise. Our final invitation list comprised 156 experts, who were contacted via email by MEM and CPG between 9th and 13th June 2025. To encourage participation, two reminder emails were issued during the survey period.

3.2. Initial expert consultation: Identifying and Prioritising Pain Points

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

- **Background information:** Captured participants' domain expertise (e.g., birds, marine mammals), years of experience, geographic and environmental focus, and professional role.
- **Hardware and software usage:** Collected data on the types of PAM hardware and software used, including specific tools for species identification, metadata management, and AI model deployment.
- **Pain points:** 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 MEM, MP, and CPG to ensure clarity and relevance. It was administered online and distributed via email between 9th and 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 were able to skip questions, resulting in variation in response numbers across items. A total of 42 respondents completed the survey, with responses per question ranging from 33 to 42.

3.3. Analysis and prioritisation of Pain Points

Quantitative and qualitative analyses were undertaken to identify, synthesise, and prioritise key challenges in PAM workflows. Qualitative responses to open-ended questions were first analysed using an inductive thematic approach. In total, nine broad challenges were reported across all experts and subsequently synthesised through an iterative coding process. Challenges

were grouped based on conceptual similarity, with overlapping items merged and terminology standardized (see Supplementary Material Questionnaires). Coding and categorisation were conducted by MEM and refined through discussion until agreement was reached, resulting in a consolidated set of nine core pain points.

This synthesised set was then shared with all 42 PAM experts via email in August 2025 for validation, ensuring completeness and accurate representation of the issues identified. Following validation, quantitative ranking data provided by participants were aggregated to generate a total severity score for each pain point, enabling comparison of relative importance and identification of the most critical bottlenecks in PAM workflows.

3.4. Follow-up expert consultation: Strategies to Minimise Pain Points

We developed and distributed a second survey instrument to identify practical strategies for addressing the challenges identified in the initial consultation. The online Qualtrics survey was distributed via email by CPG to the same pool of 42 PAM participants in August 2025, with 24 experts completing the questionnaire.

The survey instrument comprised open-ended questions designed to elicit both current practices and future-oriented solutions. To minimise ordering bias, the list of identified pain points was randomised for each participant. For each pain point, experts were asked to: (1) describe existing tools, methods, and practices currently used to address the issue, and (2) outline what an ideal, yet realistic, future solution would look like.

Responses were analysed using an iterative qualitative synthesis approach. The core team reviewed and consolidated responses by grouping similar strategies, standardising terminology, and removing redundancies. The resulting synthesis was then circulated to the 24 PAM experts who completed the second survey via email on 20th October 2025 for validation, refinement, and identification of any gaps or overlooked areas. Through this iterative feedback process, we reached consensus on a final set of recommended strategies to address each pain point, including both currently available solutions and priority areas for further development.

All co-authors reviewed and approved the final list of pain points and proposed solutions, ensuring shared ownership and alignment with community needs. For each pain point, we document at least one illustrative case study of existing practices or tools to address that challenge (see Box 1).

4. Results

4.1. Demographic Overview of Survey Respondents

Overall, we received complete sets of answers from 30 PAM experts. Most experts were academic researchers (87%), with the remaining from industry or from government agencies. The majority of experts had >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). Most respondents have collected data in Europe (31%), South America (25%), and North America (22%), following up were 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 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).

4.2. Pain points for analysing PAM data

The experts identified nine overarching themes derived from 122 individual text entries describing key pain points in PAM workflows (see *Supplementary Material Questionnaires* for categorisation of text responses). *AI-based species identification* emerged as the most critical challenge, receiving the highest cumulative 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 pointing 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 answers from multiple experts, indicating a broad and interrelated set of challenges currently limiting the scalability and adoption of PAM.

4.2.1. AI Species Identification (Total Score: 105 – Highest Priority)

Improving how we use deep learning models and AI more broadly to identify species accurately and efficiently was voted as the most urgent challenge in PAM. Across ecosystems, PAM is hampered by error rates in automated species identification (Barré et al. 2019, Metcalf et al. 2022). The performance of AI models greatly varies across taxa, regions, recorders, and recording conditions, especially in the presence of dialect variation, intra-specific variability, or species with similar calls, as well as background noise in aquatic 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 to train or benchmark models, as annotating is a time-demanding process that requires great expertise in the studied species. In the absence of open, standardised calibration datasets and geographically diverse training data, even models 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.

4.2.1.1. Current Strategies in Use

A widely endorsed approach 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 (e.g., Bell et al. 2026, Ghani et al. 2023; Huang et al. 2022, Márquez-Rodríguez et al. 2026, Williams et al. 2025). This strategy allows researchers to leverage the robustness of established models while addressing persistent gaps in taxonomic and regional coverage, including poorly represented taxa (see SI Guide 1: *Expanding BirdNET models to non-avian species through transfer learning*) and situations where labelled training data are scarce or unavailable using model embeddings and clustering approaches (see SI Guide 2: *Building acoustic classifiers with little or no labelled training data*). To further mitigate the scarcity of annotated data, particularly for rare or understudied species, several experts highlighted the use of data augmentation techniques to artificially expand training datasets (see SI Guide 3: *Data augmentation in PAM workflows*).

Experts also consistently emphasized that automated detection alone is insufficient for reliable inference, underscoring the need for workflows that combine AI-based classification with targeted manual validation (see SI Guide 6: *Accounting for classifier errors to make correct ecological inferences*). Practical strategies included prioritising subsets of detections for expert review, applying biologically informed thresholds and statistical filters (e.g., Knight et al. 2017, Wood and Kahl 2024, Wood and Peery 2022), and using ensemble approaches that combine outputs from multiple models to reduce error rates (Pérez-Granados et al. 2023). Collaboration emerged as a cross-cutting solution. Respondents 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 FishSounds (Looby et al. 2022) and the Global Library of Underwater Biological Sounds (GLUBS; Parsons et al. 2024).

4.2.1.2. Emerging Solutions

Looking ahead, respondents converged on 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. Many experts also called for built-in uncertainty metrics and user-friendly interfaces that would allow ecologists without coding skills to confidently assess and adapt 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” detectors may be aspirational, respondents saw clear potential in scalable frameworks that integrate local adaptation, ensemble modelling, and transparent reporting, allowing AI species identification to mature into a robust, reliable tool for global biodiversity monitoring.

4.2.2. 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.

4.2.2.1. Current Strategies to Manage Workflow Fragmentation

Respondents highlighted that the main way to cope with workflow fragmentation today is by manually stitching together disconnected tools while trying to maintain 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 (see SI Guide 4: *Coding an integrated multi-tool workflow in R*), while others use modular platforms like Arbimon, PAMGuard, Raven, or EcoSoundWeb to cover as many steps as possible in one place. A recurring strategy is to enforce standardised file formats (e.g., CSV, metadata schemas) to reduce incompatibilities, and to adopt relational databases or

dashboards for centralised visualisation and reporting. Users also mentioned creating custom templates and Standard Operating Procedures (SOPs) to maintain reproducibility across teams, while some collaborate directly with software developers to encourage compatibility. Despite these strategies, respondents acknowledged that fragmentation often still requires substantial manual work, and that maintaining pipelines remains time-consuming.

4.2.2.2. Emerging Solutions

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 akin to ArcGIS or QGIS for acoustics, where all modules interconnect but can also be updated independently as methods evolve. Several suggested a cloud-based infrastructure, offering scalability for large datasets, automated documentation of workflows, and real-time collaboration across teams. Respondents emphasized that such a platform should adopt universal standards for annotation formats, acoustic features, and metadata, while remaining flexible enough for local adaptation. Importantly, respondents emphasized that the future platform must be user-friendly and either open source or have commercial licensing models reserved exclusively for corporate use. Since completion of the survey, development toward such a modular PAM platform has begun within the Raven environment. However, key aspects remain absent or unclear, including cost of access, support for multi-user collaboration, the ability to search similarity among embeddings, and integrated data storage capabilities.

4.2.3. *User-Friendly Software (Total Score: 65)*

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 Rhinehart et al. 2024 for an overview of available bioacoustics software).

4.2.3.1. Current Strategies

Researchers often rely on GUI-based tools (e.g., BirdNET, Kaleidoscope, Raven, Arbimon, PAMGuard, Triton, and WildTrax). However, each has limitations in taxonomic coverage, transparency, or accessibility due to cost. A common strategy is to combine these GUI tools with tutorials, training workshops, and shared annotated R/Python scripts (e.g., R Markdown for R and Jupyter notebooks for Python) to help non-programmers bridge gaps. Some researchers reported developing their own Shiny Apps or coding add-ons to provide step-by-step guidance (see SI Guide 5: *Developing GUI-based interfaces for PAM*), while others highlighted collaboration with computer scientists as an effective way to access more advanced tools.

Another recurring theme was the need for clear documentation, reproducible guides, and community support to make existing software more approachable for ecologists and managers with limited coding experience.

4.2.3.2. Emerging Solutions

Looking ahead, respondents 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, respondents hope for software ecosystems that shift the focus away from technical hurdles and back to ecological interpretation and conservation impact.

4.2.4. 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. There is therefore a strong need for integrated validation environments that preserve the critical role of expert judgement while making manual review faster, more consistent, and more collaborative.

4.2.4.1. Current Strategies

To cope with the heavy burden of manual validation, respondents emphasized combining automation with selective human oversight. Many use tools such as BirdNET, Raven Pro, Triton, DetEdit, Arbimon, and Kaleidoscope, often integrating them with custom scripts to streamline spot-checking and label editing. A recurring strategy is to validate only subsets of detections, prioritising uncertain or low-confidence outputs, or using statistical models (e.g., occupancy models) to account for detection errors instead of exhaustively verifying every prediction (see SI Guide 6: *Accounting for classifier errors to make correct ecological inferences*). Others recommended clear annotation guidelines, training multiple users to share the load, or employing consensus approaches to reduce subjectivity. Several also highlighted the importance of open-access, pre-validated datasets that allow users to benchmark models and minimise repetitive

validation work (see Pérez-Granados et al. 2025). Active learning and filtering approaches (e.g., focusing on species known to occur at certain locations or start reviewing high-probability predictions for presence/absence) are practices currently implemented to reduce time and effort without losing reliability, as well as citizen science initiatives (e.g., Forest Listeners project; Google Arts & Culture n.d.).

4.2.4.2. Emerging Solutions

Experts 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 or 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.

4.2.5. *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. File formats, although most projects use .WAV, 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 painful 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, or synchronising annotations, which greatly reduces the degree of interoperability among projects. These issues reduce reproducibility, increase overhead, and make it hard to contribute to broader meta-analyses or cumulative research efforts.

4.2.5.1. Current Strategies

Respondents described a mix of stop-gap solutions for managing and sharing large acoustic datasets. Many rely on external hard drives, SSDs, NAS systems, and fragmented cloud storage (e.g., Box, Google Drive, Amazon Web Services, Arbimon, WildTrax) or repositories (e.g., Zenodo) to store and transfer data. For some teams, a common workaround is to use compressed, open formats (e.g., FLAC), although most use original, non-compressed formats (e.g., .WAV). Some emphasised the importance of adopting metadata standards, including file naming, (e.g.,

Darwin Core (Wieczorek et al. 2012), GUANO (Riggs, 2018) or Tethys (Roch et al. 2013),) to improve interoperability (SI Guide 7: *Using metadata standards for acoustic data management*). Overall, strategies remain fragmented and resource-dependent, with special difficulties in the Global South where backup capacity is limited.

4.2.5.2. Emerging Solutions

Although depositing sound files in well-established sound archives is still a recommended and incentivized practice (Toledo et al. 2015, Dena et al. 2018, Mendoza-Henao et al. 2021), experts 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, respondents 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.

4.2.6. *Standardisation and Comparability (Total Score: 35)*

Despite the diversity of tools and platforms for processing PAM data (e.g. 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, with few tools including calibration routines or reference levels to allow for instrument comparability. Major differences also exist between terrestrial and aquatic research, reflecting the distinct characteristics and monitoring requirements of these environments. In addition, required metadata fields, and their structure, differ widely between software tools, and users commonly struggle to merge datasets without extensive cleaning. What is needed are community-driven standards for data formats, analysis parameters, and reporting structures, perhaps with minimal but enforceable core requirements to ensure interoperability and data longevity.

4.2.6.1. Current Strategies

Respondents highlighted that the lack of standardisation is a persistent barrier but suggested practical steps to improve comparability. Many stressed the importance of precise reporting of study design, hardware, and software parameters to allow further replicability and comparisons, following the path of MANTA (“Making Ambient Noise Trends Accessible”, Miksis-Olds et al. 2021). Some recommend adopting core sets of metrics that can be consistently reported across projects, while leaving flexibility for study-specific needs. Such adoption could start with current existing metadata standards (e.g., Darwin Core, ISO initiatives, Acoustical Society of America

guidelines; see SI Guide 7: “*Using metadata standards for acoustic data management*”) and develop best-practice protocols that are easy to follow. However, this is further complicated by requirements that often vary across regions and realms. Implementing collaborative approaches, such as workshops, international networks, and cross-project benchmarking exercises, is an effective tool for promoting transparency and alignment across studies (see e.g. Wall et al. 2025).

4.2.6.2. Emerging Solutions

Experts 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 (Van der Graaf et al 2012)) will contribute to the required standardisation. There was broad consensus that an open, published international standard, broken down by group of taxa, environments, or regions, would greatly improve reproducibility and ecological synthesis, enabling PAM outputs to be compared meaningfully across scales.

4.2.7. 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 like spectrogram loading 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.

4.2.7.1. Current Strategies

Respondents described a range of pragmatic and collaborative strategies to overcome computational barriers in PAM analyses. Experts 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, experts 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 also emphasised the importance of realistically planning PAM data collection to match available computational resources, as well as integrating parallel processing and lightweight R or Python pipelines to maximise efficiency on standard desktop or laptop computers.

486 4.2.7.2. Emerging Solutions

487 Looking ahead, experts envisioned user-friendly, cloud-based platforms with equitable access to
488 computational resources as the long-term goal for supporting PAM workflows at scale. Ideally,
489 these platforms would provide free or low-cost access, particularly for researchers and
490 conservation groups in the Global South, while integrating parallel processing, containerisation,
491 and built-in optimisation to handle very large datasets efficiently. Some respondents also pointed
492 to the potential of shared or distributed computing approaches, in which idle processing capacity
493 could be pooled across institutions, drawing inspiration from citizen science models such as
494 SETI@home (Anderson et al. 2002). However, no current platform fully addresses these needs.
495 Existing solutions such as Arbimon offer several elements of this approach, but uncertainty over
496 continued free access and limited cross-platform flexibility in the classifiers that can be applied
497 deter some users from full adoption. As such, the broader vision of fully integrated, cloud-ready
498 PAM platforms capable of handling very large datasets efficiently remains largely unrealised.

499 4.2.8. Cost and Licensing (Total Score: 15)

500 Cost and licensing constraints remain a significant barrier to the uptake and scalability of PAM
501 workflows, particularly for researchers with limited funding or institutional support. Many
502 widely used PAM and bioacoustics platforms rely on proprietary licenses, with annual fees
503 typically ranging from hundreds to several thousand USD per user or project, depending on
504 functionality and data volume, which can restrict access to advanced features or limit team-wide
505 use. In addition, cloud-based processing introduces recurring costs for storage, computing, and
506 data transfer, which can quickly accumulate to hundreds or thousands of USD per year for
507 projects managing large acoustic libraries or supporting collaborative access. Together, these
508 costs can force reliance on outdated or poorly maintained free tools. In this context, open-source
509 software with permissive licenses and transparent infrastructure costs is essential for ensuring
510 equitable access to PAM tools and for supporting reproducible and globally inclusive
511 methodological innovation.

512 4.2.8.1. Current Strategies

513 Respondents emphasised that many effective free or open-source tools are already available,
514 such as BirdNET, Arbimon, Perch, PAMGuard, PamGUIDE, MANTA, RavenLite, R, and
515 Python packages. Where proprietary tools exist (e.g., Kaleidoscope Pro, Raven Pro, Matlab),
516 researchers often rely on free versions, discounted licenses, or region-specific exemptions (e.g.,
517 Raven Pro licenses for researchers in the Global South). Many also favor open-source workflows
518 by coding in R or Python, creating their own scripts, or sharing tools via GitHub, Zenodo or
519 other public repositories (SI Guide 10: *Reproducible scientific workflows for PAM*).
520 Collaborative approaches, such as negotiating team-wide licenses, forming networks to apply for
521 funding, or using institutional access, were also suggested as ways to reduce individual costs and
522 ensure broader accessibility. Overall, there is a strong culture of working with and promoting
523 free, open alternatives wherever possible.

4.2.8.2. Emerging Solutions

Experts envision a future where all PAM processing tools are free, open-source, and sustainably supported, ensuring equity across research communities worldwide. While this remains largely aspirational at present, many responses called for long-term, publicly funded support models to maintain and update free tools, with possible tiered systems where companies pay licenses but non-profit and academic researchers have free access. Others stressed the importance of building a unified, open-source PAM platform that is modular, user-friendly, and well-maintained, rather than fragmented tools with limited funding. Suggestions included government or philanthropic sponsorship, collaborative funding networks, and infrastructure to ensure transparency and reusability. The overarching goal is to remove licensing barriers, promote global equity, and accelerate collaboration and innovation in PAM.

4.2.9. Visualisation and Reporting Tools (Total Score: 6 – Lowest Priority)

While not the top concern, experts agreed that it is challenging to turn PAM data into clear, actionable insights. Many tools lack effective visualisation options, such as to display 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. Better integration with camera-trap outputs, environmental metadata, and mobile-friendly platforms would enhance usability and communication. While this category had the lowest total score, its identification as a pain point highlights its importance in supporting uptake and outreach beyond the research community.

4.2.9.1. Current Strategies

To overcome gaps in visualisation and reporting, many experts reported relying on a mix of tools (e.g., Audacity, Raven, BirdNET-Analyser GUI, PAMGuard, Triton) and custom R and Python scripts using open-source packages (e.g., seewave, warbleR, monitoR). Business intelligence software (e.g., Power BI) and R Shiny dashboards are also emerging as ways to create interactive, shareable reports (see SI Guide 5: *Developing GUI-based interfaces for PAM*). Integrating PAM outputs with environmental metadata, eDNA, or camera trap data is challenging (Lombardo et al. 2026), and currently requires bespoke coding solutions. Collaborative platforms like Arbimon and WildTrax provide partial solutions by linking PAM with other ecological data, but fragmentation remains.

4.2.9.2. Emerging Solutions

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 (Dantzker et al 2025, Rountree et al. 2020). Respondents 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.

5. Conclusions and future directions

We conducted a survey with PAM experts to highlight current challenges faced in PAM workflows, along with current strategies and emerging solutions. While experts identified nine pain points, a recurring message was that solutions already exist, in part, for most of the challenges. 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 central theme across all categories is the need for interoperability. Whether in AI model development, metadata standards, or visualisation platforms, respondents 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.

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, respondents 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.

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.

609 Table 1: Summary of key pain points in passive acoustic monitoring (PAM) workflows (ordered
610 by their importance), with corresponding short descriptions, current strategies reported by
611 experts, and envisioned ideal future solutions.

Pain Point	Score	Summary	Current Solutions	Ideal Future Scenario
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.	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.	Manually stitch tools together; use R/Python pipelines; modular platforms (Arbimon, PAMGuard, Raven, EcoSoundWeb); enforce metadata/file standards; SOPs for reproducibility.	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.	GUIs like BirdNET, Raven, Arbimon, PAMGuard, Kaleidoscope, WildTrax; combine with R/Python scripts, Shiny Apps, workshops; collaborate with computer scientists.	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	External drives, SSDs, NAS, fragmented cloud (Box, AWS, Arbimon, WildTrax); compress files; adopt metadata standards appropriate for acoustic data; FTP	Centralised, open-access repositories with standardised metadata; affordable, renewable-powered cloud storage; regional data nodes; free

		and metadata hinder reuse.	servers; ship drives in low-bandwidth areas.	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, 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.

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Overcoming software bottlenecks for scalable passive acoustic monitoring: insights from a global expert assessment

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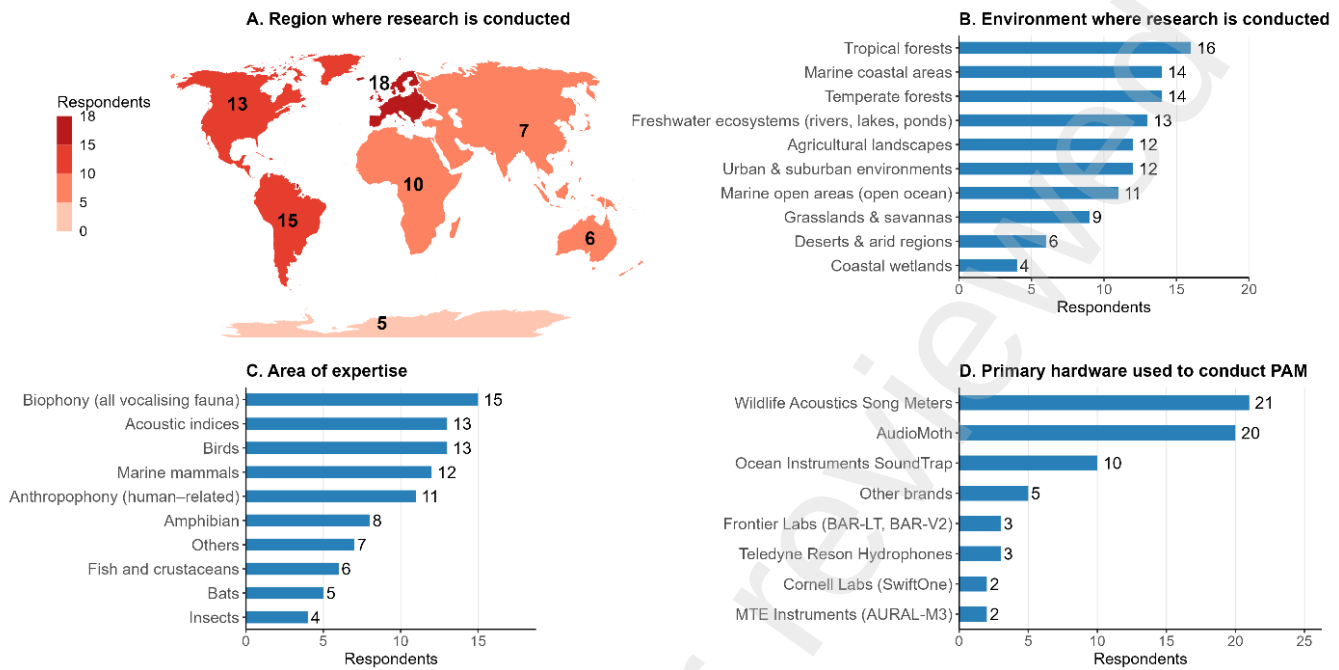


Figure 1: Geographic regions (A), research environments (B), areas of expertise (C) and hardware types used (D) reported by survey respondents ($n = 42$). Values indicate the number of respondents selecting each category, and respondents could select multiple options.

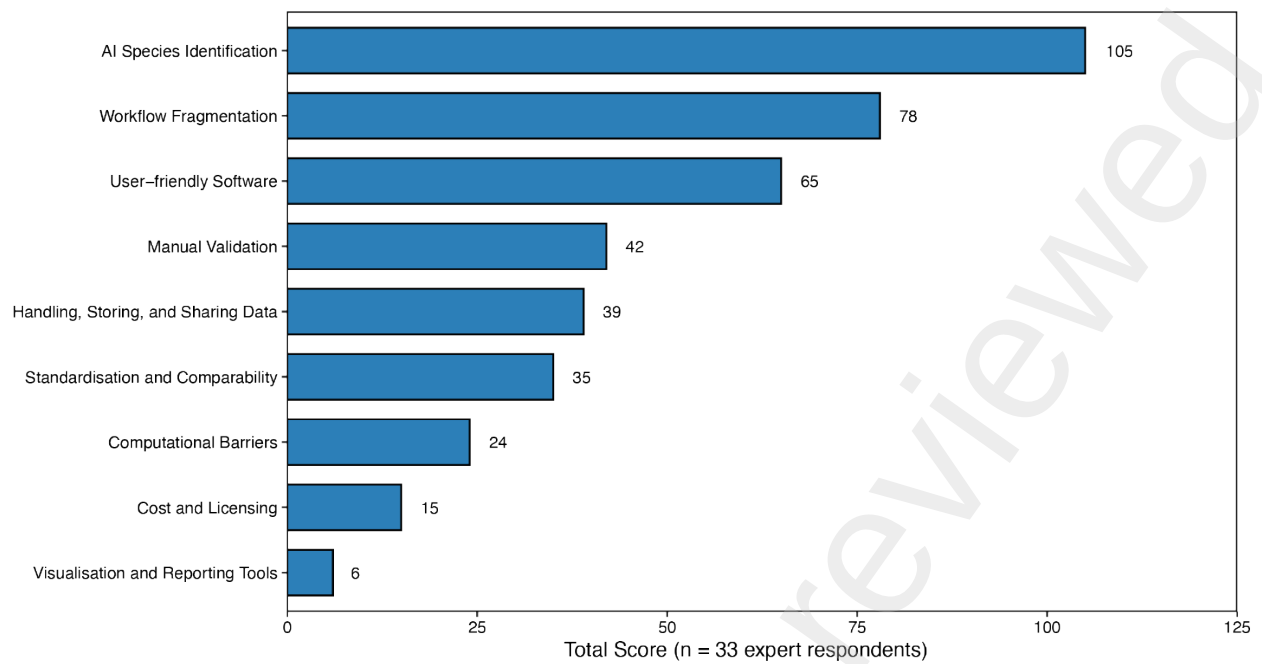


Figure 2: Total perceived importance of key pain points in passive acoustic monitoring (PAM) workflows, ranked by expert respondents. Each bar represents the cumulative score for a broad category of challenges, weighted from 5 (most important) to 1 (least important) according to respondents' rankings. Categories are ordered by total score from highest to lowest.