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ORIGINAL RESEARCH

Using mobile device built-in microphones to monitor bats: a new opportunity for large-scale participatory science initiatives

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Abstract
Citizen science has become a crucial tool in biodiversity monitoring, often facilitated by the diffusion of mobile devices, such as smartphones and tablets. High costs of professional equipment often limit large-scale monitoring, particularly in bat monitoring programmes based on acoustic surveys. Here we present the potential of using mobile devices for bat monitoring, allowing for large-scale, volunteer-based monitoring programmes. We initially compared mobile devices' performance with a professional bat detector for recording low-frequency bat calls. We then conducted a citizen science pilot study to test the method's feasibility in a real-world setting, recording echolocation and social calls of nine European bat species. We found high similarity in spectrogram quality (0.74 ± 0.09 for Samsung, 0.90 ± 0.01 for Huawei, 0.86 ± 0.09 for Xiaomi, 0.69 ± 0.09 for Apple) and average peak frequency (differences of 0.2 ± 0.5 kHz for Samsung, 0.1 ± 0.7 kHz for Huawei, 0.5 ± 1.0 kHz for Xiaomi, 0.1 ± 0.8 kHz for Apple) between calls recorded by mobile devices and professional bat detectors. The number of recorded bat calls per sampling session was also similar. However, differences in sound quality and effectiveness among mobile device brands were found. iOS devices outperformed professional detectors at recording bat calls at increasing distances. The citizen science pilot study tested 35 mobile device models, all of which effectively recorded bats. This study suggests that mobile devices could be an accessible, no-cost tool for large-scale bat monitoring. Incorporating mobile devices into existing monitoring networks or creating new dedicated programmes could not only enhance data collection, but also boost public knowledge and awareness about bats, ultimately promoting informed decision-making and better conservation strategies.

Keywords Acoustic monitoring · Bats · Citizen science · Low-cost methods · Monitoring programmes · Smartphones

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Introduction

The involvement of the public in scientific research is spreading rapidly around the globe and may become essential to monitor biodiversity and the environment (De Rijck et al. 2020). Participatory science initiatives delegate research phases to volunteers, varying from data collection to problem definition and result dissemination (Bristol 2013). These initiatives are used in various biology fields including ecology, and offer advantages in data collection, coverage, timing, and cost, yielding exceptional results (De Rijck et al. 2020). For example, the eBird platform collects over 100 million annual bird sightings from around 700,000 users, significantly boosting research and conservation efforts (www.ebird.org). Xeno-canto, a global platform for sharing wildlife sound recordings, has recently introduced the possibility to upload real-time recordings of Orthoptera and bats, alongside bird sounds (www.xeno-canto.org).

Mobile devices are integral to daily life in the digital age. In 2021, smartphones and tablets dominated the mobile device market, making up over 80% (O'Dea 2022a). By 2025, it is expected that 71% of the global population will own smartphones (GSMA 2018), and experts predict smartphones might replace computers due to their portability and versatility (Nie et al. 2020). In this study, "mobile device" refers to smartphones and tablets.

Participatory science initiatives often use mobile devices to quickly reach a large audience, collect and analyse data, and connect scientists and citizens (Land-Zandstra et al. 2015). Thanks to the internet connection, mobile devices are used to record observations and send them to a central project database (Aristeidou and Herodotou 2020). In addition, camera, microphone, and location services allow citizen scientists to transmit multimedia content tagged with geospatial information (Aristeidou et al. 2021).

Bats are the second largest order of mammals, occurring nearly everywhere in the world and providing critically important ecosystem services as agents of pest suppression, pollination, and seed dispersal (Ramírez-Fráncel et al. 2022). Nowadays, bats are under severe threat from several factors such as habitat destruction and degradation, use of pesticides, urban development, climate change, invasive species, hunting, and persecution (Frick et al. 2020). Several international agreements (e.g., UNEP/EUROBATS, Habitats Directive 92/43/EEC, Bonn Convention), as well as national and international organisations for bat conservation (e.g., Bat Conservation International in USA, Australasian Bat Society in Australia, Bat Conservation Trust in UK, Bat Conservation India) have been established in every continent (https://www.eurobats.org/). Nevertheless, our knowledge of most bat species is still inadequate (Welch and Beaulieu 2018), even though 80% of bat species assessed by IUCN require conservation or research attention (Frick et al. 2020). Large-scale monitoring programmes are essential to understand the ecological needs of bat populations and test the efficacy of conservation plans.

Bioacoustics is widely used to monitor bats in their environment, answer ecological questions and suggest conservation actions (Lopez-Baucells et al. 2021). Automatic bat detectors allow researchers to simultaneously carry out full-night monitoring sessions at multiple sites, massively reducing sampling time and cost, resulting in large amounts of data collected (Roemer et al. 2021). Furthermore, advances in the analysis of full-spectrum recordings (Barataud 2020) and continuous development of automatic classifiers (Barré et al. 2019) have brought many amateurs, researchers, environmental consultancies, and government agencies closer to this world, encouraging cooperation.

The growing need for long-term, large-scale bat monitoring programmes, combined with the relative ease of use of automatic bat detectors, has led in the last years to the establishment of regional- and national-scale participatory science initiatives entirely based on passive acoustic monitoring (PAM). These projects generally rely on volunteers borrowing automatic bat detectors and conducting acoustic sampling sessions at fixed points or along transects. Examples are the Norfolk Bat Survey in the UK (Newson et al. 2015) and the Vigie-Chiro programme in France (Kerbiriou et al. 2015). The North American Bat Monitoring Program (NABat) incorporates various participatory survey types in its methodology, including both mobile and stationary acoustic surveys (Loeb et al. 2015). Newly introduced USB ultrasound microphones, which enable mobile devices to be turned into professional bat detectors (Christmann 2014; Unger et al. 2019), have further expanded the opportunities for public engagement in bat monitoring (Hughes et al. 2021). In the realm of affordability and portability, AudioMoth stands out, enabling bat monitoring with adjustable sample rates up to 384 kHz, at a relatively low cost (Hill et al. 2018). However, although we are moving towards portable, user-friendly, and low-cost detectors (Beason et al. 2019; Zamora-Gutierrez et al. 2021), device cost is still a significant limit. Ranging from a few hundred to over $1,000 per unit, the budget required to purchase multiple devices can make large-scale citizen science projects impractical (Hill et al. 2018).

The highest sound sampling rate supported by most mobile devices is 44.1 or 48 kHz (Chen et al. 2017). Based on the Nyquist-Shannon sampling theorem (Shannon 1949), they cannot pick up sound at a frequency higher than 22 or 24 kHz, respectively. However, this relatively low-frequency limit may be high enough to record echolocation or social calls of some bat species. In Europe, *Tadarida teniotis* emits echolocation calls with frequency at maximum energy (FME) of 11–12 kHz when flying in open spaces (Rydell and Arlettaz 1994). Echolocation calls of the three Euopean *Nyctalus* species fall below 24 kHz as well, especially when flying in open space (Estók and Siemers 2009; Buckley et al. 2011). Social calls of *Pipistrellus kuhlii* have a typical FME of 14 kHz (Piskorski and Sachanowicz 2021). In Africa, *Otomops harrisoni* echolocates at an FME of 12 kHz (Wilson and Mittermeier 2019). In North America, Rodhouse et al. (2021) demonstrated that *Euderma maculatum* echolocation calls and *Antrozous pallidus* social calls could be detected by unaided human ear, enabling monitoring of these species through coordinated citizen science aural surveys.

In this study, we present the potential of mobile devices to record low-frequency bat calls through their built-in microphones and compare the performance of mobile devices versus professional bat detectors in recording these types of calls. To our knowledge, no prior studies have tested or considered this method. Furthermore, we assess the feasibility and applicability of this approach by launching a citizen science pilot project, requesting volunteers to record low-frequency bat calls using their smartphones or tablets. Aiming to implement this method at national or international level, this approach paves the way for entirely new opportunities in future large-scale citizen science projects.

Materials and methods

Simultaneous monitoring via mobile devices and bat detector

The efficacy of mobile devices in recording low-frequency bat calls was evaluated through three primary methodologies: quantification of collected recordings, assessment of recording quality, and determination of call detectability. In all cases, the performance of mobile devices was compared to that of a professional bat detector (Wildlife Acoustics Song Meter Mini Bat), which acted as a control.

In the first phase of the study, mobile devices and the bat detector were deployed simultaneously in the field, and the number of recordings collected by each device during each sampling session was compared to the number of recordings collected by the bat detector.

Modern mobile devices feature micro-electromechanical system (MEMS) microphones, ideal for their compact size, low power consumption, and clear sound quality. Despite the standard technology used in these microphones, variations in components like the back chamber volume, membrane materials, and sound entry port design can affect their sensitivity and frequency response (Shah et al. 2019). These specifications often differ based on the device brand and model (Zamora et al. 2017), leading to significant differences in acoustic parameters obtained (Marsano-Cornejo and Roco-Videla 2022). To address potential differences in microphone quality and sensitivity, we selected a range of device models from the most widely used brands in the market. In 2021, Apple and Samsung accounted for nearly half of the mobile device market, followed by a few Android OS-based brands whose popularity has increased in recent years, such as Xiaomi and Huawei (O'Dea 2022b). Based on this background information, 13 mobile device models were selected, of which 5 iOS (Apple) and 8 Android (3 Samsung, 3 Xiaomi and 2 Huawei; Table 1).

Where possible, mobile devices were configured to operate as automatic bat detectors, initiating brief recordings whenever the detected frequencies and sound intensities exceeded pre-set thresholds. On Android devices, this was achieved using the Bat Recorder app (https://digitalbiology.com/bat-recorder), originally designed to record ultrasonic audio signals using a smartphone or tablet with a separately purchased USB ultrasonic microphone. Interestingly, it can also employ the Android device's built-in microphone. However, on iOS devices, the implementation of automatic sampling was not feasible. This limitation was not due to the iOS devices' inherent capabilities but the absence of apps on the iOS platform that support continuous trigger-based automatic recording using the device's built-in microphone. Consequently, we used the pre-installed Voice Memos app (https://apps.apple.com/us/app/voice-memos/id1069512134) to produce single recordings encompassing the entire sampling session and save them in a lossless compression format (.m4a extension). Recordings were then converted to WAV format and cut to a length of 10 s using 'av' and 'warbleR' packages in R (R Core Team 2020; Ooms 2021; Araya-Salas and Smith-Vidaurre 2017).

Sampling was carried out between August 2021 and October 2022 at six urban and suburban sites in Turin (Italy), avoiding excessively noisy areas. Further recording was conducted in Seville (Spain), near a large maternity colony of greater noctule (*Nyctalus lasiopterus*; Hernández-Brito et al. 2018), one of the rarest and least known bat species in Europe, very difficult to contact in Italy (Paniccia et al. 2023). Soprano pipistrelle (*Pipistrellus pygmaeus*) was also recorded in the same area. Sampling was carried out with no rain or wind, from sunset to up to 4 h later. Both bat detector and mobile devices were mounted

Table 1 Mobile device models used in comparison with the bat detector to test their efficacy in recording low-frequency bat calls. The table shows in which analysis each model was used: all 13 models were used in the first two analysis, and ten of them were used in the analysis of call detectability

ID	OS	Brand	Model	Model name	Comparison of number of calls	Analysis of call similarity	Analysis of detectability
1	Android	Huawei	FIG-LX1	Huawei P smart	✓	✓	✓
2	Android	Huawei	HMA-L29	Huawei Mate 20	✓	✓	
3	Android	Samsung	SM-A515F	Samsung Galaxy A51	✓	✓	✓
4	Android	Samsung	SM-G950F	Samsung Galaxy S8	✓	✓	✓
5	Android	Samsung	SM-T819	Samsung Galaxy Tab S2	✓	✓	✓
6	Android	Xiaomi	M1908C3XG	Xiaomi Redmi Note 8T	✓	✓	
7	Android	Xiaomi	M2003J6B2G	Xiaomi Redmi Note 9 Pro	✓	✓	✓
8	Android	Xiaomi	M2010J19SY	Xiaomi Redmi 9T	✓	✓	✓
9	iOS	Apple	A1530	Apple iPhone 5 S	✓	✓	
10	iOS	Apple	A2105	Apple iPhone XR	✓	✓	✓
11	iOS	Apple	A2218	Apple iPhone 11 Pro Max	✓	✓	✓
12	iOS	Apple	A2296	Apple iPhone SE	✓	✓	✓
13	iOS	Apple	A2633	Apple iPhone 13	✓	✓	✓

next to each other on top of 2.5-m vertical poles, under the open sky and at least 3 m away from obstacles. The automatic bat detector was set to record in full spectrum, with a sample rate of 384 kHz and a continuous duty cycle; minimum trigger frequency was set to 8 kHz, maximum recording length to 10 s, trigger window to 3 s, and gain to 12 dB (maximum settable value). Mobile devices also recorded in full spectrum at a default sample rate of 48 kHz. The Bat Recorder app enabled Android devices to be set to record automatically based on a minimum trigger frequency of 8 kHz and trigger intensity threshold of -40 dB (minimum settable value, i.e. maximum possible sensitivity). Pre-trigger of 1 s, post-trigger of 3 s, and maximum recording length of 10 s were also set. Recording on iOS devices via the Voice Memos app started at the beginning of the sampling session and stopped at the end, resulting in a single long recording to be trimmed later.

All recordings from both bat detector and mobile devices were manually analysed using BatSound (https://batsound.com). Acoustic analysis of the entire dataset was conducted by one of the authors (F.G.), and to ensure accuracy, a blind check of 20% of recordings was carried out by an external expert operator (E.P.), who confirmed the identifications. Species identification was performed following methods described by Barataud (2020), Russ (2021), and Middleton et al. (2022). Full details are provided in Appendix S1.

As a first assessment of the effectiveness of mobile devices in recording low-frequency bat calls, the total and species-specific number of bat recordings collected during each session were compared to those recorded by the bat detector using the Wilcoxon signed rank test.

Analysis of call similarity

Cross-correlation analysis was performed to quantify the similarity between spectrogram-like representations of bat calls recorded by mobile devices and the same calls recorded by the bat detector. A subset of recordings collected during the first phase of the study was used. Only species for which at least 5 recordings were available for at least 3 mobile device models (of which at least 1 Android and 1 iOS) were considered. For each species, 5 to 20 recordings for each model were selected with their matching recordings collected by bat detector, where possible across multiple sampling sessions to homogenise the sample.

Pairs of matching sequences, comprised of the same sequence recorded by a mobile device model and the bat detector, were saved as separate audio files using BatSound, and intervals between calls were silenced where needed (i.e., in case of presence of background noise). A band-pass filter of 8–24 kHz was applied to all sequences to isolate the target frequency range. This means frequencies below 8 kHz and above 24 kHz were removed from each audio file. Sequences recorded by bat detector were then downsampled from 384 kHz to 48 kHz, to allow for cross-correlation analysis. Filtering and downsampling were performed in Praat (Boersma 2001). After audio file preparation, single calls within each sequence were automatically detected based on amplitude, duration, and frequency range attributes using the 'warbleR' package in R. A customised amplitude threshold-setting approach was employed for detecting calls due to the varying ratio between the intensity of background noise and the calls in recordings. Each recording was first manually checked to note the expected call count. Multiple threshold levels (ranging from 2 to 70) were then tested for each recording to identify the optimal threshold. The appropriate threshold was determined when the detected call count matched the manual count, and the intervals between detected calls were consistent across both the bat detector and mobile device recordings. Following these steps, the calls were extracted and saved for cross-correlation analysis. Pearson's correlation between call pairs was then performed using 'soundgen' package (Anikin 2019). Welch's *t*-test and Welch's one-way ANOVA were used to assess significant differences in correlation coefficients across mobile device OSs and models, the latter further supplemented by the Games-Howell post-hoc test for pairwise comparisons.

As an additional measurement of call similarity, we calculated the differences in mean peak frequency between call pairs, after measuring the mean peak frequency of each call using the 'warbleR' package. Measurements relative to the peak frequency are less variable, making it a key acoustic parameter for species identification (Kraker-Castañeda et al. 2020). The Wilcoxon signed rank test was employed to compare the mean peak frequency between call pairs. To assess whether differences in mean peak frequency between call pairs varied significantly across mobile device OSs and models, Welch's *t*-test and Welch's one-way ANOVA were used, the latter further supplemented by the Games-Howell post-hoc test for pairwise comparisons.

Detectability of bat calls based on distance

In the third phase of the study, the performance of mobile devices in detecting potential bat calls at increasing distances was compared to that of the bat detector. Ten of the 13 mobile device models selected in the first phase of the study were used in this phase (4 iOS and 6 Android; Table 1). Reference full-spectrum echolocation and social call sequences of potential target species selected from Russ (2021) and Middleton et al. (2022) were played back at real-time speed on Avisoft UltraSoundGate Player BL Light speaker using Avisoft-RECORDER USGH 4.3.04 software. Call sequences known to be only emitted inside roost and those from bats held in hand were not used, as the method is intended to be used to monitor free-flying bats. Similarly, sequences composed of signals whose frequencies were only partially within the range detectable by mobile devices were not considered. Where necessary, basic audio editing was performed on reference call sequences using BatSound, to make them suitable for the test. This could involve extracting specific intervals, removing unwanted noises and species, and adjusting volume. A total of 32 reference call sequences belonging to 21 European bat species were used (Appendix S2).

The test was performed in daytime in a 150-m stretch of an unused road outside Turin. The speaker was placed at a fixed position on a 1.2 m table. Bat detector and mobile devices were placed on another 1.2 m table, located at exponentially growing distances from the source (2, 4, 8, 16, 32 and 64 m). All devices' microphones were pointed towards the playback speakers, with 0° angle in relation to the ground. At every distance, a playlist containing the selected call sequences was played back, with 10s silence intervals between each one and the next. Bat detector and Android devices were set to record automatically, with the same settings as in the first phase of the study. On iOS devices, single recordings lasting the playlist duration were carried out; each call sequence was then extracted based on playback timing using 'warbleR' package in R. For both sets of recordings, manual checks were conducted using BatSound. A recording was considered valid if: (a) the sequences were completely visible on the spectrogram, ensuring that even the weakest signal portions were captured and not lost due to the distance from the ultrasonic emitter, and (b) the essential acoustic parameters for species identification – including FME, start frequency (SF), end frequency (EF), and duration – matched those of reference recordings. A Poisson Generalised Linear Model (GLM) using a logarithmic link function was fitted for each device model, where the response variable was the count of detected call sequences, and the explanatory variable was the distance from source. The model results were used to generate call sequence count predictions for a sample of 1,000 distances ranging from 2 to 64 m. Predictions were then used to draw distance response curves for all device models. A two-way ANOVA was employed to assess the effect of device model on the efficacy of recording call sequences at increasing distances.

Citizen science pilot study

To confirm the method's applicability and to test the success of more mobile device models in recording bat calls, a citizen science pilot project was carried out between 2020 and 2022 in Northern Italy. A standardised sampling protocol was developed (Appendix S3), providing guidelines for acoustic data collection using Bat Recorder or Voice Memos app with the same settings used in the first phase of the study. Volunteers were asked to carry out 1–5 sampling sessions, recording automatically (Android) or continuously (iOS) from sunset to up to 4 h later. Collected recordings were then sent to the authors, with information on the device model used, location, date and time of start and end of sampling. Manual analysis of all recordings aimed at species identification was performed as described in paragraph 2.1. Data collected in the first phase of the study were also included in this analysis, as data collection methods were the same.

Results

Species identification and quantification of collected recordings

A total of 25 sessions of simultaneous acoustic monitoring were carried out. Of these, 17 sessions were carried out using Android devices and 8 using iOS devices. Average recording session duration was 2.46 ± 1.53 h, the longest one lasting 6.42 h. The total number of low-frequency bat recordings collected by bat detector and by mobile devices were 5,776 and 5,339, respectively. According to Wilcoxon signed rank test, the number of bat recordings per sampling session was not significantly different when recorded by mobile device or bat detector. This similarity held true both for the total number of bat recordings and for the number of recordings of each individual species in each session. In 15 sessions and with 11 different models, mobile devices collected more bat recordings than the bat detector. Considering Android devices (set to automatic recording mode as the bat detector), average ratio of bat recordings to the total number of collected recordings (used as a proxy for correct triggering) was 0.39 ± 0.32 for bat detector and 0.33 ± 0.32 for mobile devices. In total, 8 species were recorded by mobile devices and confirmed by bat detector: *H. savii*, *N. lasiopterus*, *N. leisleri*, *N. noctula*, *P. kuhlii*, *P. nathusii*, *P. pygmaeus* and *T. teniotis*. On mobile devices, *Hypsugo* and *Pipistrellus* species were identified by their type D social calls (Nardone et al. 2017; Middleton et al. 2022). For *P. nathusii*, only part *a* of the typical type D social call was recorded, as parts *b* and *c* are higher in frequency and therefore out of mobile device detectability range. *Nyctalus* and *Tadarida* species were identified by their echolocation calls (Fig. 1). In addition, *N. noctula* type D2 social calls (fast trills; Middleton et al. 2022) were recorded on one occasion (29/09/2021, using Samsung Galaxy Tab S2). In 91% of cases, species recorded by mobile devices matched those recorded by bat detector within the 8–24 kHz range. On 2 out of 13 sessions, *T. teniotis* was recorded by mobile device but not by bat detector. On the other hand, *N. leisleri* was recorded by bat detector but not by mobile device on 1 out of 6 sessions, and the same was true for *N. noctula* on 1 out of 13 sessions. *P. kuhlii* was the species recorded in most sessions (n = 18), while *H. savii* and *P. pygmaeus* were only recorded in one session.

Analysis of call similarity

For the analysis of call similarity, 1068 pairs of bat calls were selected from a total of 221 pairs of sequences across five species: *N. lasiopterus* (n = 82), *N. leisleri* (n = 27), *N. noctula* (n = 341), *P. kuhlii* (n = 384), and *T. teniotis* (n = 234). Although the number of available calls was small, *N. leisleri* was included in the analysis to evaluate possible limitations in recording bats emitting near the upper limit of mobile device detectability range. Cross-correlation results are summarised in Fig. 2. Average Pearson correlation coefficients between mobile device and bat detector call spectrograms were as follows: 0.74 ± 0.09 for Samsung, 0.90 ± 0.01 for Huawei, 0.86 ± 0.09 for Xiaomi, 0.69 ± 0.09 for Apple. In 70% of cases, Pearson correlation was higher than 0.70. The number of correlation coefficients below 0.70 was evenly distributed between iOS and Android devices. However, over 90% of these cases were associated with calls recorded by Samsung devices for the Android platform. The lowest correlation coefficient for Huawei devices was 0.87, while only one of the three Xiaomi models used (Xiaomi Redmi Note 8T) had coefficients lower than 0.80.

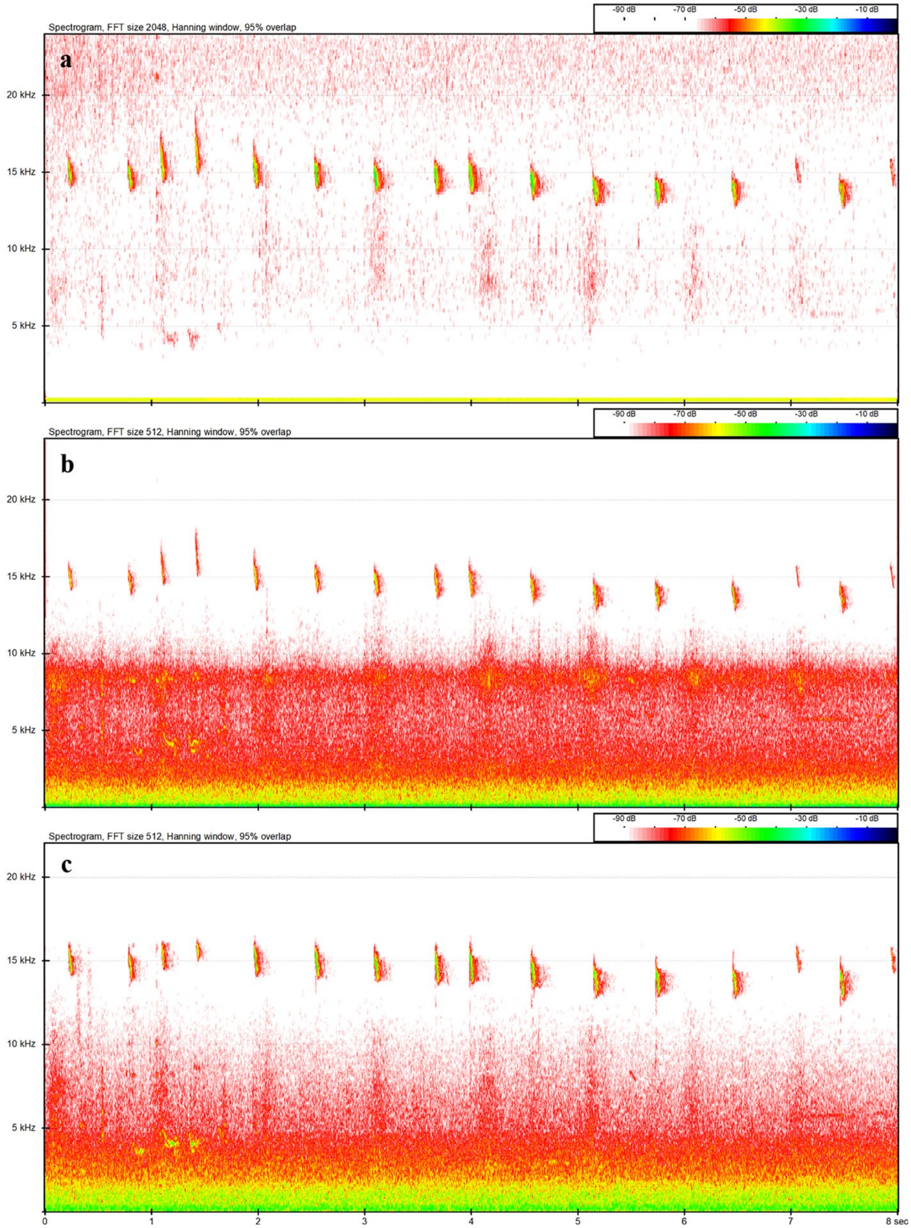

Fig. 1 Spectrogram of a sample recording depicting an echolocation sequence of *N. lasiopterus* (Seville, 13/10/2021). The sequence was simultaneously recorded using (**a**) a professional bat detector (Wildlife Acoustics Song Meter Mini Bat), (**b**) an Android device (Samsung Galaxy S8), and (**c**) an iOS device (Apple iPhone 5 S). In each graph, the X-axis shows time in seconds, the Y-axis shows frequency in kHz, and the colour gradient shows sound intensity in decibels (blue for high sound intensity, and white/red for low intensity). Spectrogram images were generated using BatSound

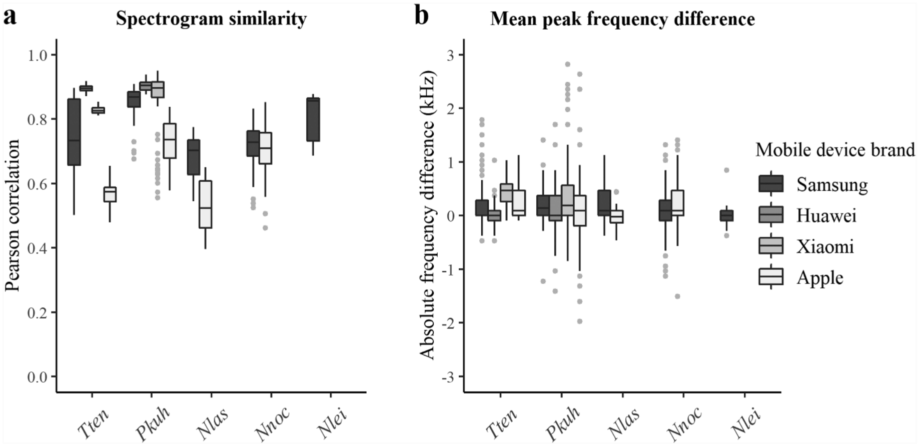

Fig. 2 Similarity between call pairs, each pair consisting of the same call recorded by a mobile device and the bat detector. (**a**) Results of cross-correlation analysis between mobile device and bat detector call spectrograms: for each mobile device brand, correlation coefficients are shown. (**b**) Differences in call mean peak frequency between mobile device and bat detector, grouped by mobile device brand. In both graphs, boxes indicate the 25th and 75th percentiles, middle lines indicate the medians, and whiskers indicate the non-outlier values; grey circles represent the outliers. Only species for which enough call pairs were available were used. Species abbreviations (and number of call pairs used) are as follows: *Tten*=*Tadatida teniotis* (*n*=234); *Pkuh*=*Pipistrellus kuhlii* (*n*=384); *Nlas*=*Nyctalus lasiopterus* (*n*=82); *Nnoc*=*Nyctalus noctula* (*n*=341); *Nlei*=*Nyctalus leisleri* (*n*=27). Although the number of available calls was small, *N. leisleri* was included in the analysis to evaluate possible limitations in recording bats emitting near the upper limit of mobile device detectability range. On the X-axis, species are listed in order of increasing typical peak frequency

According to Welch's *t*-test, correlation coefficients for calls recorded by iOS devices were significantly lower than those recorded by Android devices ($p<0.001$, Cohen's d = -0.90). Additionally, Welch's one-way ANOVA showed a significant overall difference in correlation coefficients among the 13 device models ($p<0.001$), and the Games-Howell post-hoc test identified significant differences between model pairs even within the same brand (refer to Appendix S4.a for all pairwise comparisons). No decrease in average correlation was observed when considering species emitting at higher frequencies (i.e., closer to the upper limit of mobile device detectability range). According to Wilcoxon signed rank test, the call mean peak frequency was significantly different when recorded by mobile device or bat detector ($p<0.001$). However, differences measured on each call pair were less than 1.0 kHz in 93% of cases, and less than 0.5 kHz in 82% of cases (Fig. 2). Average differences varied depending on the mobile device brand considered: 0.2 ± 0.5 kHz for Samsung, 0.1 ± 0.7 kHz for Huawei, 0.5 ± 1.0 kHz for Xiaomi, 0.1 ± 0.8 kHz for Apple. Welch's *t*-test indicated that these differences were significantly smaller for calls recorded on iOS devices compared to those recorded on Android devices ($p<0.05$, Cohen's d = -0.13), while Welch's one-way ANOVA showed they varied significantly across the 13 device models ($p<0.001$). The Games-Howell post-hoc test identified significant differences between a few model pairs, some of which within the same brand (refer to Appendix S4.b for all pairwise comparisons).

Analysis of detectability

The predicted distance response curves based on the results of detectability test are shown in Fig. 3. A two-way ANOVA revealed a significant main effect of device model on recording call sequences at increasing distances ($p < 0.001$). Android devices performed generally worse compared to the bat detector, whereas iOS devices showed higher performance, especially at high distance from source. Up to 16 m, bat detector and iOS devices performed very similarly, picking up all or nearly all the 32 reference call sequences; among Android devices, Huawei and Xiaomi performed better, picking up from 22 to 30 call sequences at 16 m, whereas Samsung devices picked up from 12 to 21. At 32 m, bat detector only picked up 13 call sequences, while iOS devices still picked up from 21 to 29; except for one model (Xiaomi Redmi 9T), which picked up 22, Android devices picked up from 3 to 10 call sequences. No call sequences were recorded by bat detector at 64 m, but all iOS devices and the Xiaomi Redmi 9T were still able to pick up from 4 to 14 call sequences (full results are available in Appendix S5). For all mobile devices, call sequences whose frequency was near the upper limit of detectability range (24 kHz) were the first to go undetected as distance from the source increased.

Citizen science pilot study

Thanks to the citizen science pilot, we were able to test the method on 35 mobile device models belonging to 7 brands (Huawei, LG, Meizu, Motorola, Samsung, Xiaomi, and Apple). One to five recording sessions were performed for each model, for a total of 80 recording sessions. Average recording session was 3.09 ± 1.95 h. In total, 9,117 bat recordings were collected, belonging to 9 species. These included the 8 species which were identified in the first phase of the study, in addition to *P. pipistrellus*, whose type D social calls (Middleton et al. 2022) were confidently identified on a total of 201 recordings made by 3 different mobile device models. All models recorded at least one, and up to 7 species. *P. kuhlii* was recorded by 34 models, followed by *T. teniotis* ($n = 25$), *N. leisleri* ($n = 12$) and *N. noctula* ($n = 11$). On a few occasions, type C.d1 (male advertisement calls; Middleton et al. 2022) and type D2 social calls of *N. leisleri* were recorded (Appendix S6: Figs. S12-S13). A total of 102 recordings remained unidentified, mainly due to the impossibility to view the whole calls as they straddled the upper limit of mobile device detectability range. Five models (Huawei

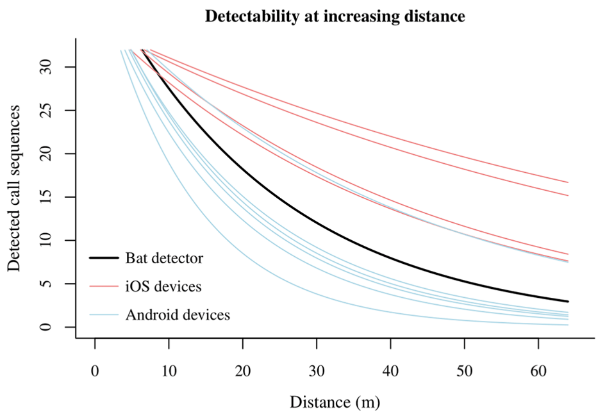

Fig. 3 Predicted distance response curves for bat detector, Android, and iOS devices resulting from detectability analysis. Call sequence count predictions were generated for each device model using Poisson GLMs

Mate 20, Huawei P10, Samsung Galaxy A7, Xiaomi Redmi 8, and Xiaomi Redmi Note 8) produced aliasing artifacts (Appendix S6: Fig. S17).

Discussion

This study demonstrated the potential of using mobile devices as a cost-effective method for monitoring bat activity and species richness. Within the detectability range of 8–24 kHz, mobile devices almost always recorded the same species recorded by the bat detector, showing no significant difference in the number of bat passes per session. This indicates that mobile devices, when properly set up, can detect low-frequency bat calls with comparable effectiveness to bat detectors. However, significant variability has been observed among mobile device models in terms of detection capability and quality of recordings produced. When using this monitoring method, it is therefore essential to consider the device operating system and model.

The Wildlife Acoustics Song Meter Mini Bat, a widely popular bat detector, was used as a control tool during the tests. As sensitivity and performance can vary among different bat detectors (Adams et al. 2012; Kunberger and Long 2023), results might differ if the tests were carried out using alternative models. In the Song Meter Mini Bat, the maximum gain that can be set is 12 dB, whereas in other detectors it can be higher (Kaiser and O'Keefe 2015). Increasing gain beyond this limit may therefore allow for weaker call detection. However, this could also produce more noise and false detections (trigger activated by mistake; Kunberger and Long 2023). On Android devices, sensitivity was maximised by setting the trigger intensity threshold to minimum. This resulted in more bat passes but also more false detections being recorded. Continuous recording via iOS devices resulted in a large volume of non-bat recordings, requiring more time for manual identification. Conversely, many weak calls that failed to trigger bat detector and Android devices were recorded. However, it is important to recognise that continuous recording is not a practical approach for bat acoustic monitoring. The automatic mode, which selectively records sounds likely to be from bats, is crucial in this context. It helps save storage space, reduces time required for acoustic analysis, and significantly improves the method's practicality and suitability for large-scale monitoring projects. Additionally, conducting single, long-duration recordings poses a considerable risk. Should the device's battery run out and the device subsequently powers down, the recording is not saved, resulting in the potential loss of several hours of collected data. In contrast, automatic monitoring ensures the immediate saving of each individual recording, typically lasting a few seconds. This means the device can be left to record until the battery is fully depleted with the assurance that all data collected up to the point of the device shutdown is securely saved. For these reasons, the development of both Android- and iOS-compatible apps that support automatic monitoring is essential to standardise the methodology and enhance acoustic analysis efficiency in future research. Such apps could potentially include features like correction curves tailored to different mobile devices. This would help mitigate audio distortions that occur during recording, thereby enhancing the comparability of data obtained from various devices.

Acoustic monitoring through bat detector usually requires a lot of storage space, as recording at a high sample rate results in very large audio files (Baloch et al. 2021). This issue is significantly reduced when using mobile devices, as they record at a lower sample rate. Based on data collected in this study, audio files generated by mobile devices occupied, on average, 10% (Android) and 15% (iOS) of the space required by files produced by bat detector.

In our study, nine European bat species were identified using low-frequency echolocation or social calls. However, the potential for identifying a greater number of species, particularly through their social calls, is considerable. For instance, during the selection of reference recordings for the detectability test, 21 out of the 44 species known to occur in Europe were considered (Russ 2021), indicating that many more species could potentially be identified.

Globally, there is evidence that at least some bat species on every continent emit echolocation or social calls within the frequency range recordable by mobile devices. Among echolocation calls, low-frequency emitters are mostly found in the Emballonuridae, Molossidae, and Vespertilionidae families. Notable examples include species from the *Diclidurus*, *Eumops*, and *Nyctinomops* genera in the Americas (Jung et al. 2007; Zamora-Gutiérrez et al. 2016; Arias-Aguilar et al. 2018; Bohn and Gillam 2018), species from the *Mops* and *Tadarida* genera in Africa, Asia, and Australia (Milne 2002; Kingston et al. 2003; Pennay et al. 2004; Taylor et al. 2005, 2013; López-Bosch et al. 2021), along with other species like *Otomops martiensseni* in Africa (Taylor et al. 2005), *Idionycteris phyllotis* in America (Zamora-Gutiérrez et al. 2016), and *Ozimops lumsdenae* and *Saccolaimus flaviventris* in Australia (Milne 2002; Pennay et al. 2004).

Social calls, typically lower in frequency than echolocation calls and often audible to humans (Fenton 2003), expand the range of detectable species across various families. In the Americas, species from Emballonuridae, Molossidae, Mormoopidae, Phyllostomidae, Rhinolophidae, and Vespertilionidae families are known for their low-frequency social calls (Bohn and Gillam 2018; Springall et al. 2019; Lattenkamp et al. 2021; Reyes and Szewczak 2022). Similarly, in Africa and Asia, species from Megadermatidae, Molossidae, Rhinolophidae, and Vespertilionidae families have been documented with these calls (Csada 1996; Fenton et al. 2004; Luo et al. 2017a, b). Notably, some species, like *Eumops floridanus* in Florida, emit both echolocation and social calls within the detectable range of mobile devices (Bohn and Gillam 2018). However, the understanding of bat social calls remains limited, especially in some regions, suggesting the potential for a broader range of detectable species and families.

Importantly, several detectable species are of conservation concern. *Mops johorensis* is classified as Vulnerable (Senawi et al. 2020), and *Tadarida latouchei* as Endangered (Thong and Loi 2020), according to The IUCN Red List of Threatened Species. For others, like *Tadarida aegyptiaca*, distribution ranges are not fully understood (Monadjem et al. 2017). The monitoring method described in this study could play a crucial role in filling these knowledge gaps, thereby aiding in the conservation of these species.

Frequency and structure of bat echolocation calls can vary a lot in relation to multiple factors including habitat, physiology, and behaviour (Jones and Teeling 2006). Usually, quasi-constant frequency (QCF) calls have a lower and more stable frequency (bandwidth < 5 kHz), as well as a more regular pattern of repetition, compared to frequency modulated (FM) calls, which can facilitate manual identification (Barataud 2020). However, when hunting or flying in cluttered environments, these species can adapt their calls by increasing both frequency and bandwidth to gather more information about the shape and position of prey and obstacles (Barataud 2020). In such instances, the start frequency (SF) may exceed the mobile device's upper limit of detectability and the initial portions of some calls might be lost, making identification difficult or even impossible. In some cases (e.g., *N. leisleri* flying in clutter), frequencies may be high enough for the species to go undetected. Social calls of several species may also be subject to the same issue (Middleton et al. 2022). Recording environment should therefore be taken into careful consideration during sampling design. To optimise the number of recordable species and increase chances of obtaining high-quality recordings using mobile devices, it is advisable to conduct acoustic sampling in open areas wherever possible. In more cluttered environments, such as forests, seeking out areas that are relatively open, like clearings, roads, or trails, can significantly enhance sampling effectiveness and recording quality.

Improvements in mobile device technology, such as increased frequency response and sensitivity, could further expand the range of detectable species. Chen et al. (2017) investigated the ability of mobile devices to detect ultrasounds beyond their typical 24 kHz limit, using a novel method based on coprime sampling. Further developments of this approach might open new frontiers for mobile devices in ultrasound recording, potentially enhancing their use in bat monitoring as well.

In recent years, the introduction of USB ultrasound microphones and other low-cost detectors has made bat monitoring more accessible to the public and researchers (Blackburn and Unger 2019). There have been numerous participatory science initiatives employing both USB ultrasound microphones (Robinson and Robinson 2021; Smirnov et al. 2023; Metcalfe et al. 2023) and AudioMoth devices (Lundberg et al. 2021). However, the cost of these devices, ranging from just under a hundred to several hundred dollars per unit, can still be a substantial barrier for many organisations and research groups. This financial constraint highlights the need for continued efforts in making bat monitoring tools more affordable and accessible. Our study explored the practicality of conducting bat monitoring using only mobile devices, a method that, while limited to certain bat species, does not necessitate additional equipment purchases, making it an immediately viable option.

Future research and development may help speeding up the identification process. Machine learning algorithms could be employed to automate the analysis of large datasets, potentially overcoming time limitations of manual analysis (Russo and Voigt 2016). However, caution should always be taken when approaching the use of automatic classifiers. While they offer efficiency, their accuracy should always be validated against expert-verified datasets to ensure reliability. Misidentification risks, particularly in complex acoustic environments, underscore the importance of ongoing validation and refinement of these tools (Rydell et al. 2017).

Another potential direction may be exploring the use of mobile devices for real-time monitoring and analysis of bat activity. This could be achieved by developing dedicated mobile apps that can process and analyse bat calls directly on the device, providing immediate feedback to users and allowing for adaptive sampling strategies. Currently, there are applications that perform similar functions, such as the BatSound Touch app by Pettersson (https://batsound.com/product/batsound-touch/), and the Echo Meter Touch Bat Detector app by Wildlife Acoustics (https://play.google.com/store/apps/details?id=emtouch.wildlifeacoustics.com.echometer).

The analysis of spectrogram similarity supports the accuracy of mobile devices in recording bat calls. Cross-correlation analysis between call pairs showed a high degree of similarity in most cases. Lower correlation for calls recorded by iOS devices may be attributed to variations in analog-to-digital conversion (ADC) and digital signal processing (DSP) mechanisms, as well as OS-specific factors (Boulanger and Lazzarini 2011). Minor differences in call similarity, and potentially in peak frequency, might be attributed to the effects of downsampling of bat detector recordings (Casaseca-de-la-Higuera et al. 2015). Significant differences in correlation were found between device brands and models, highlighting the importance of considering this factor when analysis data collected by mobile devices. However, lower correlation does not necessarily imply lower efficiency. Notably, we observed that both the number of recordings and detection range of iOS devices exceeded those of the bat detector. No decrease in average correlation was observed for species emitting at higher frequencies, suggesting good accuracy even when recording calls close to the upper limit of mobile device detectability range. Most times, small differences in measured peak frequency (i.e., less than 0.5 kHz) are not a major issue for species identification (Kraker-Castañeda et al. 2020). However, this magnitude of variation may become more relevant in regions with high species richness, where there is an increased likelihood of overlapping acoustic parameters among different species (López-Baucells et al. 2016). In such environments, to minimise the risk of misidentification, it is advisable to gather reference recordings from mobile devices for all species that are potentially detectable in the area. This preparatory step should ideally be undertaken before launching large-scale monitoring projects using mobile devices, ensuring a more accurate and reliable identification process.

Bat call detectability was found to significantly differ based on the mobile device used, with iOS devices exhibiting similar performance to one another and generally outperforming Android devices. While continuous recording on iOS devices may have captured more weak or distant calls, analysis was focused only on sequences with measurable key acoustic parameters necessary for accurate species identification. Therefore, any sequences recorded on iOS devices experiencing loss of the weakest signal components due to excessive distance from the ultrasonic emitter were not considered. This approach effectively addressed potential variations in detectability on iOS devices due to continuous recording. However, variability in detectability performance might also be linked to differences in the frequency response curves of the microphones used in mobile devices and the bat detector (Forbes and Newhook 1990). Such differences in hardware, along with ADC and DSP mechanisms and other OS-specific factors (Boulanger and Lazzarini 2011), may indeed have affected the efficiency and accuracy of bat call detection across different devices. The reference recordings used belonged to 21 European bat species, and many of them were social calls. The inability of mobile devices or the bat detector to detect certain sequences beyond a specific distance does not necessarily represent the actual detectability limit for those signals or species in the wild. In fact, this was largely influenced by the conditions and device used for the original recordings, as well as the speaker settings during playback in the tests. Consequently, some sequences may have been excessively amplified, while others may have been insufficiently amplified. The primary purpose of the test was to evaluate and compare the performance of the bat detector and mobile devices under identical conditions, rather than establishing the actual detection range for those specific sequences in the wild. However, an interesting observation was that calls with higher frequencies, particularly those nearing the upper limit of the mobile devices' detectability range, tended to be the first to become undetectable as the distance from the source increased. This phenomenon is likely a consequence of the well-known physical principle that higher frequency sounds attenuate more rapidly with distance (Griffin 1971).

The citizen science pilot study allowed for field testing of the monitoring protocol. We observed significant variations in the duration of sampling sessions. Although the protocol specified that sampling should be conducted for at least four hours from sunset, sometimes sessions were shorter. This could be due to battery life issues, or the participant's inability or unwillingness to spend an entire evening without access their phone (Kaplan Mintz et al. 2023). Citizen science data also allowed for the method to be tested on a significantly larger number of device models. Results showed that all mobile devices used could record bats, producing sequences of adequate quality for species-level identification. However, due to the considerable variability in detection capability and recording quality across different models, incorporating a preliminary detectability test into the sampling protocol may be beneficial. In the framework of large-scale participatory initiatives, pre-launch tests should be conducted using a professional bat detector as a control. These tests should aim to collect reference recordings of species that are detectable within the target area, ideally sampling from various sub-regions. Such approach would also allow for the documentation of potential acoustic variations in echolocation pulses and dialects in social calls (Prat et al. 2017; Sun et al. 2020). Additionally, we stress the importance of manual verification of species identifications. While initial phases of acoustic analysis might involve volunteer participation or the use of an automatic classifier, we advocate for a subsequent validation of at least a portion of the identifications by an expert. This approach is crucial to ensure the accuracy and reliability of the data collected. Despite these technological constraints, the substantial volume of data that participatory initiatives can generate holds great promise for expanding our understanding of bat populations and their behaviour, contributing valuable insights to the field of bat research.

This study demonstrates the potential of using mobile devices as a cost-effective and widely accessible tool for bat monitoring. By incorporating mobile devices into new or ongoing bat monitoring networks and initiatives, we could leverage the full potential of this method, supporting fully volunteer-based monitoring. Engaging citizens in bat monitoring can help raise awareness about bat ecology and conservation, fostering a sense of responsibility and stewardship among the public (Peter et al. 2019). This, in turn, can contribute to more informed decision-making and conservation efforts at various levels, from local communities to policymakers (MacPhail and Colla 2020). The combination of the mobile device approach with public participation could potentially revolutionise bat monitoring, allowing for more extensive and efficient data collection, while also promoting bat understanding, protection, and conservation.

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Data availability All bat recordings collected by mobile devices can be accessed on Dryad at: https://doi.org/10.5061/dryad.2280gb5z4.

Declarations

Competing interests The authors have no relevant financial or non-financial interests to disclose.

References

Adams AM, Jantzen MK, Hamilton RM, Fenton MB (2012) Do you hear what I hear? Implications of detector selection for acoustic monitoring of bats. Methods Ecol Evol 3:992–998. https://doi.org/10.1111/j.2041-210X.2012.00244.x

Anikin A (2019) Soundgen: an open-source tool for synthesizing nonverbal vocalizations. Behav Res Methods 51(2):778–792. https://doi.org/10.3758/s13428-018-1095-7

Araya-Salas M, Smith-Vidaurre G (2017) warbleR: an R package to streamline analysis of animal acoustic signals. Methods Ecol Evol 8(2):184–191. https://doi.org/10.1111/2041-210X.12624

Arias-Aguilar A, Hintze F, Aguiar LMS, Rufray V, Bernard E, Pereira MJR (2018) Who's calling? Acoustic identification of Brazilian bats. Mamm Res 63(3):231–253. https://doi.org/10.1007/s13364-018-0367-z

Aristeidou M, Herodotou C (2020) Online Citizen Science: a systematic review of effects on Learning and scientific literacy. Citiz Science: Theory Pract 5(1):11. https://doi.org/10.5334/cstp.224

Aristeidou M, Herodotou C, Ballard HL, Young AN, Miller AE, Higgins L, Johnson RF (2021) Exploring the participation of young citizen scientists in scientific research: the case of iNaturalist. PLoS ONE 16(1):e0245682. https://doi.org/10.1371/journal.pone.0245682

Baloch JA, Jumani AK, Laghari AA, Estrela VV, Lopes RT (2021) A Preliminary Study on Quality of Experience Assessment of Compressed Audio File Format. 2021 IEEE URUCON: 161–165. https://doi.org/10.1109/URUCON53396.2021.9647114

Barataud M (2020) Acoustic Ecology of European Bats. Species Identification, Study of their Habitats and Foraging Behaviour. 2nd éd. Biotope éditions, Mèze. Muséum national d'Histoire naturelle, Paris (Inventaires & biodiversité series)

Barré K, Le Viol I, Julliard R, Pauwels J, Newson SE, Julien J-F, Claireau F, Kerbiriou C, Bas Y (2019) Accounting for automated identification errors in acoustic surveys. Methods Ecol Evol 10:1171–1188. https://doi.org/10.1111/2041-210X.13198

Beason RD, Riesch R, Koricheva J (2019) AURITA: an affordable, autonomous recording device for acoustic monitoring of audible and ultrasonic frequencies. Bioacoustics 28(4):381–396. https://doi.org/10.1080/09524622.2018.1463293

Blackburn A-J, Unger S (2019) Smartphones as a non-invasive surveying tool to monitor bats. J Young Investig. 37(3):24–30. https://doi.org/10.22186/jyi.37.3.24-30

Boersma P (2001) Praat, a system for doing phonetics by computer. Glot Int 5:341–345

Bohn KM, Gillam EH (2018) In-flight social calls: a primer for biologists and managers studying echolocation. Can J Zool 96(8):787–800. https://doi.org/10.1139/cjz-2017-0188

Boulanger R, Lazzarini V (2011) The Audio Programming Book. The MIT

Bristol UWE (2013) Science for Environment Policy In-depth Report: Environmental Citizen Science. European Commission DG Environment. http://ec.europa.eu/science-environment-policy

Buckley DJ, Puechmaille SJ, Roche N, Teeling EC (2011) A critical assessment of the presence of *Barbastella barbastellus* and *Nyctalus noctula* in Ireland with a description of *N. Leisleri* echolocation calls from Ireland. Hystrix 22(1):111–127. https://doi.org/10.4404/hystrix-22.1-4472

Casaseca-de-la-Higuera P, Lesso P, McKinstry B, Pinnock H, Rabinovich R, McCloughan L, Monge-Álvarez J (2015) Effect of downsampling and compressive sensing on audio-based continuous cough monitoring. 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC): 6231–6235. https://doi.org/10.1109/embc.2015.7319816

Chen Y, Gong W, Liu J, Cui Y (2017) Fine-grained ultrasound range finding for mobile devices: sensing way beyond the 24 kHz limit of built-in microphones. 2017 IEEE Conf Comput Commun Workshops (INFOCOM WKSHPS) 845:850. https://doi.org/10.1109/INFCOMW.2017.8116486

Christmann EP (2014) Echo Meter Touch. Sci Teacher 81(8):82

Csada R (1996) Cardioderma cor. Mamm Species 519:1–4. https://doi.org/10.2307/3504163

De Rijck K, Schade S, Rubio J-M, Van Meerloo M (2020) Best practices in Citizen Science for Environmental Monitoring: Commission Staff Working Document. https://doi.org/10.25607/OBP-1779. European Commission

Estók P, Siemers BM (2009) Calls of a bird-eater: the echolocation behaviour of the enigmatic greater noctule, *Nyctalus lasiopterus*. Acta Chiropt 11(2):405–414. https://doi.org/10.3161/150811009X485620

Fenton MB (2003) Eavesdropping on the echolocation and social calls of bats. Mamm Rev 33(3–4):193–204. https://doi.org/10.1046/j.1365-2907.2003.00019.x

Fenton MB, Jacobs DS, Richardson E, Taylor PJ, White WT (2004) Individual signatures in the frequency-modulated sweep calls of African large-eared, free-tailed bats *Otomops martiensseni* (Chiroptera: Molossidae). J Zool 262(1):11–19. https://doi.org/10.1017/s095283690300431x

Forbes BC, Newhook EM (1990) A comparison of the performance of three models of bat detectors. J Mammal 71(1):108–110. https://doi.org/10.2307/1381328

Frick WF, Kingston T, Flanders J (2020) A review of the major threats and challenges to global bat conservation. Ann NY Acad Sci 1469:5–25. https://doi.org/10.1111/nyas.14045

Griffin DR (1971) The importance of atmospheric attenuation for the echolocation of bats (Chiroptera). Anim Behav 19(1):55–61. https://doi.org/10.1016/s0003-3472(71)80134-3

GSMA (2018) The mobile economy 2018. https://data.gsmaintelligence.com/api-web/v2/research-file-download?id=28999769&file=The%20Mobile%20Economy%202018.pdf (accessed on 20/11/2022)

Hernández-Brito D, Carrete M, Ibáñez C, Juste J, Tella JL (2018) Nest-site competition and killing by invasive parakeets cause the decline of a threatened bat population. Roy Soc Open Sci 5:172477. https://doi.org/10.1098/rsos.172477

Hill AP, Prince P, Covarrubias EP, Doncaster CP, Snaddon JL, Rogers A (2018) AudioMoth: evaluation of a smart open acoustic device for monitoring biodiversity and the environment. Methods Ecol Evol 9:1199–1211. https://doi.org/10.1111/2041-210X.12955

Hughes C, Brown C, Melnycky NA, Steenweg RJ (2021) Bats in my backyard: a citizen science project using the Echo Meter Touch 2 in Peace River, Alberta. Western Canada Bat Network Newsletter 36(Spring 2021): 12–17. https://sway.office.com/YDS0mXdhY3meCGiA?ref=Link&loc=play (accessed on 23/11/2022)

Jones G, Teeling EC (2006) The evolution of echolocation in bats. Trends Ecol Evol 21(4):149–156. https://doi.org/10.1016/j.tree.2006.01.001

Jung K, Kalko EKV, Von Helversen O (2007) Echolocation calls in central American emballonurid bats: signal design and call frequency alternation. J Zool 272(2):125–137. https://doi.org/10.1111/j.1469-7998.2006.00250.x

Kaiser ZDE, O'Keefe JM (2015) Data Acquisition varies by Bat Phonic Group for 2 types of Bat Detectors when weatherproofed and paired in field settings. Wildl Soc B 39(3):635–644. https://doi.org/10.1002/wsb.572

Kaplan Mintz K, Arazy O, Malkinson D (2023) Multiple forms of engagement and motivation in ecological citizen science. Environ Educ Res 29(1):27–44. https://doi.org/10.1080/13504622.2022.2120186

Kerbiriou C, Julien J-F, Bas Y, Marmet J, Le Viol I, Lorrillièr R, Azam C, Gasc A, Lois G (2015) Vigie-Chiro: 9 ans de suivi des tendances des espèces communes. Symbioses, Réseau des muséum de la région Centre n.s. 34 & 35: hal-03766876. https://gmb.bzh/wp-content/uploads/2016/03/Vigie-Chiro-Symbiose.pdf (accessed on 20/04/2023)

Kingston T, Jones G, Akbar Z, Kunz TH (2003) Alternation of Echolocation calls in 5 species of aerial-feeding Insectivorous bats from Malaysia. J Mamm 84(1):205–215. https://doi.org/10.1644/1545-1542(2003)084<0205:AOECIS>2.0.CO;2

Kraker-Castañeda C, Ku-Peralta W, Santos-Moreno A (2020) Missing something? Importance of measurement criteria of acoustic parameters in the analysis of bats recordings. J Bat Res Conserv 13(1):94–99. https://doi.org/10.14709/BarbJ.13.1.2020.15

Kunberger JM, Long AM (2023) A comparison of Bat calls recorded by two acoustic monitors. J Fish Wildl Manag 14(1). https://doi.org/10.3996/JFWM-22-028. e1944-687X

Land-Zandstra AM, Devilee JLA, Snik F, Buurmeijer F, van den Broek JM (2015) Citizen science on a smartphone: participants' motivations and learning. Public Underst Sci 25(1):45–60. https://doi.org/10.1177/0963662515602406

Lattenkamp EZ, Nagy M, Drexl M, Vernes SC, Wiegrebe L, Knörnschild M (2021) Hearing sensitivity and amplitude coding in bats are differentially shaped by echolocation calls and social calls. Proc Royal Soc B 288(1942):20202600. https://doi.org/10.1098/rspb.2020.2600

Loeb SC, Rodhouse TJ, Ellison LE, Lausen CL, Reichard JD, Irvine KM, Ingersoll TE, Coleman JTH, Thogmartin WE, Sauer JR, Francis CM, Bayless ML, Stanley TR, Johnson DH (2015) A plan for the north American Bat Monitoring Program (NABat). Gen. Tech. Rep. SRS-208. U.S. Department of Agriculture Forest Service, Southern Research Station, Asheville, NC. https://doi.org/10.2737/SRS-GTR-208

Lopez-Baucells A, Yoh N, Rocha R, Bobrowiec PED, Palmeirim JM, Meyer CFJ (2021) Optimising bat bioacoustic surveys in human-modified neotropical landscapes. Ecol Appl 31(6):e02366. https://doi.org/10.1002/eap.2366

López-Baucells A, Rocha R, Bobrowiec P, Bernard E, Palmeirim J, Meyer C (2016) Field guide to amazonian bats. Instituto Nacional de Pesquisas da Amazônia (INPA)

López-Bosch D, Huang JCC, Wang Y, Palmeirim AF, Gibson L, López-Baucells A (2021) Bat echolocation in continental China: a systematic review and first acoustic identification key for the country. Mamm Res 66(3):405–416. https://doi.org/10.1007/s13364-021-00570-x

Lundberg P, Meierhofer MB, Vasko V, Suutari M, Ojala A, Vainio A, Lilley TM (2021) Next-generation ultrasonic recorders facilitate effective bat activity and distribution monitoring by citizen scientists. Ecosphere 12(12):e03866. https://doi.org/10.1002/ecs2.3866

Luo B, Huang X, Li Y, Lu G, Zhao J, Zhang K, Zhao H, Liu Y, Feng J (2017a) Social call divergence in bats: a comparative analysis. Behav Ecol arw184. https://doi.org/10.1093/beheco/arw184

Luo B, Lu G, Chen K, Guo D, Huang X, Liu Y, Feng J (2017b) Social calls honestly signal female competitive ability in Asian particoloured bats. Anim Behav 127:101–108. https://doi.org/10.1016/j.anbehav.2017.03.012

MacPhail VJ, Colla SR (2020) Power of the people: a review of citizen science programs for conservation. Biol Conserv 249:108739. https://doi.org/10.1016/j.biocon.2020.108739

Marsano-Cornejo M-J, Roco-Videla Á (2022) Comparison of the acoustic parameters obtained with different smartphones and a professional microphone. Acta Otorrinolaringol Esp 73(1):51–55. https://doi.org/10.1016/j.otorri.2020.08.006

Metcalfe AN, Fritzinger CA, Weller TJ, Dodrill MJ, Muehlbauer JD, Yackulic CB, Holton PB, Szydlo CM, Durning LE, Sankey JB, Kennedy JA (2023) Insectivorous bat foraging tracks the availability of aquatic flies (Diptera). J Wildl Manag 87(5):e22414. https://doi.org/10.1002/jwmg.22414

Middleton N, Froud A, French K (2022) Social calls of the bats of Britain and Ireland (second edition). Pelagic Publishing

Milne DJ (2002) Key to the Bat calls of the top end of the Northern Territory. Parks and Wildlife Commission of the Northern Territory, Darwin

Monadjem A, Jacobs D, Cotterill W, Hutson AM, Mickleburgh S, Bergmans W, Fahr J (2017) *Tadarida aegyptiaca*. The IUCN Red List of Threatened Species 2017: e.T21312A22115459. https://doi.org/10.2305/IUCN.UK.2017-2.RLTS.T21312A22115459.en

Nardone V, Ancillotto L, Russo D (2017) A flexible communicator: social call repertoire of Savi's pipistrelle, *Hypsugo savii*. Hystrix 28(1):68–72. https://doi.org/10.4404/hystrix-28.1-11825

Newson SE, Evans HE, Gillings S (2015) A novel citizen science approach for large-scale standardised monitoring of bat activity and distribution, evaluated in eastern England. Biol Conserv 191:38–49. https://doi.org/10.1016/j.biocon.2015.06.009

Nie J, Wang P, Lei L (2020) Why can't we be separated from our smartphones? The vital roles of smartphone activity in smartphone separation anxiety. Comput Hum Behav 109:106351. https://doi.org/10.1016/j.chb.2020.106351

O'Dea S (2022a) Global mobile device market share in 2017 and 2021, by shipments of device type. https://www.statista.com/statistics/183530/worldwide-market-share-mobile-device/

O'Dea S (2022b) Global smartphone production volume share 2021, by brand. https://www.statista.com/statistics/742531/global-smartphone-production-volume-share/

Ooms J (2021) av: Working with Audio and Video in R. R package version 0.6.0. https://CRAN.R-project.org/package=av

Paniccia C, Zingg PE, Bellè A, Hilpold A, Reichegger F, Tappeiner U, Ladurner E (2023) Bioacoustic evidence for a continuous summer presence of the greater noctule bat, *Nyctalus lasiopterus*, in the Italian Alps. Mammal Res. https://doi.org/10.1007/s13364-022-00668-w

Pennay M, Law B, Reinhold L (2004) Bat calls of New South Wales: region based guide to the echolocation calls of microchiropteran bats. NSW Department of Environment and Conservation, Hurstville

Peter M, Diekötter T, Kremer K (2019) Participant outcomes of Biodiversity Citizen Science projects: a systematic literature review. Sustainability 11(10):2780. https://doi.org/10.3390/su11102780

Piskorski M, Sachanowicz K (2021) Different songflight calls of *Pipistrellus kuhlii* and *Pipistrellus lepidus* (Vespertilionidae, Chiroptera) in Europe. J Vertebr Biol 71:21058. https://doi.org/10.25225/jvb.21058

Prat Y, Azoulay L, Dor R, Yovel Y (2017) Crowd vocal learning induces vocal dialects in bats: Playback of conspecifics shapes fundamental frequency usage by pups. PLoS Biol 15(10):e2002556. https://doi.org/10.1371/journal.pbio.2002556

R Core Team (2020) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Ramírez-Fráncel LA, García-Herrera LV, Losada-Prado S, Reinoso-Flórez G, Sánchez-Hernández A, Estrada-Villegas S, Lim BK, Guevara G (2022) Bats and their vital ecosystem services: a global review. Integr Zool 17:2–23. https://doi.org/10.1111/1749-4877.12552

Reyes G, Szewczak JM (2022) Attraction to conspecific social-calls in a migratory, solitary, foliage-roosting bat (*Lasiurus cinereus*). Sci Rep 12:9519. https://doi.org/10.1038/s41598-022-13645-9

Robinson CV, Robinson JM (2021) Listen but do not Touch: using a Smartphone Acoustic device to investigate Bat Activity, with implications for community-based monitoring. Acta Chiropt 23(1):247–258. https://doi.org/10.3161/15081109acc2021.23.1.021

Rodhouse TJ, Rose S, Hawkins T, Rodriguez RM (2021) Audible bats provide opportunities for citizen scientists. Conserv Sci Pract 3(7):e435. https://doi.org/10.1111/csp2.435

Roemer C, Julien J-F, Bas Y (2021) An automatic classifier of bat sonotypes around the world. Methods Ecol Evol 12:2432–2444. https://doi.org/10.1111/2041-210X.13721

Russ J (2021) Bat calls of Britain and Europe: a Guide to Species Identification. Pelagic Publishing

Russo D, Voigt CC (2016) The use of automated identification of bat echolocation calls in acoustic monitoring: a cautionary note for a sound analysis. Ecol Indic 66:598–602. https://doi.org/10.1016/j.ecolind.2016.02.036

Rydell J, Arlettaz R (1994) Low-frequency echolocation enables the Bat *Tadarida teniotis* to feed on Tympanate Insects. Proc R Soc B: Biol Sci 257:175–178. https://doi.org/10.1098/rspb.1994.0112

Rydell J, Nyman S, Eklöf J, Jones G, Russo D (2017) Testing the performances of automated identification of bat echolocation calls: a request for prudence. Ecol Indic 78:416–420. https://doi.org/10.1016/j.ecolind.2017.03.023

Senawi J, Csorba G, Kingston T (2020) Chaerephon johorensis. IUCN Red List Threatened Species 2020:eT4313A22019065. https://doi.org/10.2305/IUCN.UK.2020-2.RLTS.T4313A22019065.en

Shah MA, Shah IA, Lee D-G, Hur S (2019) Design approaches of MEMS microphones for enhanced performance. J Sens 9294528. https://doi.org/10.1155/2019/9294528

Shannon CE (1949) Communication in the Presence of noise. Proc IRE 37(1):10–21. https://doi.org/10.1109/jrproc.1949.232969

Smirnov DG, Klimov AS, Numerov AD, Trufanova EI (2023) Experience in using an Echo Meter Touch Ultrasonic Module in studies of the species Composition, occurrence, and Biotopic preferences of bats (Chiroptera, Vespertilionidae) in Voronezh Oblast. Biol Bull Russ Acad Sci 50(7):1511–1524. https://doi.org/10.1134/S1062359023070245

Springall BT, Li H, Kalcounis-Rueppell MC (2019) The In-Flight social calls of Insectivorous bats: species specific behaviors and contexts of Social Call Production. Front Ecol Evol 7:441. https://doi.org/10.3389/fevo.2019.00441

Sun C, Jiang T, Gu H, Guo X, Zhang C, Gong L, Shi B, Feng J (2020) Geographical variation of social calls and vocal discrimination in male himalayan leaf-nosed bats. Anim Behav 170:15–26. https://doi.org/10.1016/j.anbehav.2020.10.003

Taylor PJ, Geiselman C, Kabochi P, Agwanda B, Turner S (2005) Intraspecific variation in the calls of some African bats (Order Chiroptera). Durb Mus Novit 30(1):24–37. https://journals.co.za/content/admn/30/1/AJA0012723X_1887

Taylor PJ, Sowler S, Schoeman MC, Monadjem A (2013) Diversity of bats in the Soutpansberg and Blouberg mountains of Northern South Africa: Complementarity of Acoustic and Non-acoustic survey methods. S Afr J Wildl 43(1):12–26. https://doi.org/10.3957/056.043.0117

Thong VD, Loi DN (2020) *Tadarida latouchei*. The IUCN Red List of Threatened Species 2020: e.T40036A22060323. https://doi.org/10.2305/IUCN.UK.2020-2.RLTS.T40036A22060323.en

Unger SD, Hickman C, Murray K (2019) Use of smartphones in science: evaluation of low cost and accessible methods to identify and study roosting bats. ECOTROPICA 21:201907. https://doi.org/10.30427/ecotrop201907

Welch J, Beaulieu JM (2018) Predicting extinction risk for data deficient bats. Diversity 10(3):63. https://doi.org/10.3390/d10030063

Wilson DE, Mittermeier RA (2019) Handbook of the mammals of the world – volume 9, bats. Lynx Edicions

Zamora W, Calafate CT, Cano J-C, Manzoni P (2017) Accurate ambient noise Assessment using smartphones. Sensors 17(4):917. https://doi.org/10.3390/s17040917

Zamora-Gutierrez V, MacSwiney G, MC, Martínez Balvanera S, Robredo Esquivelzeta E (2021) The Evolution of Acoustic Methods for the Study of Bats. In B.K. Lim, M.B. Fenton, R.M. Brigham, S. Mistry, A. Kurta, E.H. Gillam, A. Russell, J. Ortega (eds.) 50 Years of Bat Research, Fascinating Life Sciences, pp 43–59. https://doi.org/10.1007/978-3-030-54727-1_3

Zamora-Gutiérrez V, López-González C, González MH, Fenton B, Jones G, Kalko EKV, Puechmaille SJ, Stathopoulos V, Jones K (2016) Acoustic identification of Mexican bats based on taxonomic and ecological constraints on call design. Methods Ecol Evol 7(9):1082–1091. https://doi.org/10.1111/2041-210x.12556