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Crowdsourced Urban Noise Pollution Mapping App

Farel Julio Adinata Pinem[1], Alber Keane Ginting[2], Benaya Benedict Bonardo Panjaitan[3], Giselle Ruslim[4], Hanniel Emerald Kayanta Ginting[5], Kenneth Esteban Ginting[6]

SMAK 7 PENABUR Jakarta; SMAK 3 PENABUR Jakarta; SMAN 30 Jakarta, SMAN 77 Jakarta; SMA Fons Vitae 1, Jakarta, Indonesia

Email : fareljulioap28@gmail.com[1], kennethginting36@gmail.com[2], benayabenedict912@gmail.com[3], giselleruslim@gmail.com[4] , kayanta.gintingsugihen09@gmail.com[5] , albertkeaneginting@gmail.com[6]

Abstract

Jakarta experiences persistent environmental noise driven by rapid urbanization, traffic, and commercial activity, while conventional manual sampling cannot capture continuous daily acoustic variation. This study evaluates AudioHome, a mobile application for automated and crowdsourced urban noise mapping. A quantitative design was applied at four Jakarta observation locations: Cempaka Putih Timur, Cipinang Indah Raya, the Matraman Bus Corridor, and Kawasan Pulomas. Decibel readings were paired with location coordinates and timestamps across multiple daily intervals, with the inverse-square law used as a theoretical basis for interpreting sound propagation. The results show the highest recorded average at the Matraman Bus Corridor (75 dB), followed by Cipinang Indah Raya (72 dB), while Cempaka Putih Timur reached interval values up to 65 dB and Kawasan Pulomas recorded 58 dB. AudioHome supports real-time logging, historical review, map-linked records, trend visualization, CSV export, and automated advocacy reporting. These findings indicate that smartphone-based crowdsourced sensing can provide accessible evidence for identifying urban noise hotspots and supporting community and municipal responses.

Keywords: noise pollution, crowdsourced, noise mapping, environmental acoustics, Jakarta soundscapes

1. Introduction

1.1. Background and Research Gap

Behind Jakarta's traffic congestion and dense urban development lies a persistent environmental hazard: a high and often continuous level of sound. Rapid population growth, traffic, construction, commercial activity, and widespread loudspeaker use contribute to elevated ambient noise. Prolonged exposure is associated in the source manuscript with reduced concentration, stress, fatigue, sleep disruption, and longer-term health risks.

The problem is especially relevant to learning environments. A study conducted at MTs Negeri 34 Jakarta reported that traffic noise entering classrooms disrupted teaching and student concentration. Teachers had to raise their voices or pause lessons when loud vehicles passed, illustrating how environmental noise can directly affect the learning process [4].

Indonesia regulates environmental noise through the Decree of the Minister of Environment No. 48 of 1996. The source manuscript highlights a 55 dBA limit for educational zones, yet routine monitoring still relies heavily on periodic manual measurements. Such short sampling periods may miss sudden traffic peaks and daily acoustic fluctuations, limiting the evidence available for enforcement and local decision-making [5].

This study addresses that gap by evaluating AudioHome, a mobile application intended to automate noise measurement and combine decibel readings with time and location data. The central proposition is that a crowdsourced urban noise mapping application can function both as a diagnostic tool for identifying noise patterns and as a participatory platform that supports context-specific noise-reduction responses by communities and local authorities.

1.2. Related Research and Theoretical Basis

Previous studies establish the health and urban-planning relevance of environmental noise. Gupta et al. reported that children are particularly sensitive to chronic noise and described effects involving learning, memory, stress, sleep, and hearing, recommending measures such as quieter zoning and soundproofing in schools and residential areas [3]. Vianna, Rodrigues, and Cardoso found that urban traffic noise was strongly associated with annoyance and poor sleep, particularly when respondents were at home or at work [2]. Martono, Sukar, and Sulistiyani

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reported high traffic-noise levels in the Jakarta area, including an average of 78.85 dBA at roadside points and 67.24 dBA at residential points 80 meters from major roads [7].

In this study, noise pollution is treated as excessive or disturbing environmental sound that interferes with normal human activity. Noise mapping refers to the systematic measurement and visualization of sound-level distribution across defined locations, while crowdsourcing refers to the participation of many distributed users in collecting observations through a digital platform. Recent smartphone-based environmental noise research shows that this model can generate large georeferenced datasets, although data quality depends on device characteristics, calibration, measurement context, and post-processing [10]-[13].

The theoretical basis also includes the inverse-square law. In an open environment, sound intensity decreases as distance from the source increases, following an inverse-square relationship. The source manuscript notes that doubling distance from a sound source can reduce the sound level by approximately 6 dB under ideal conditions. This relationship provides a physical basis for interpreting spatial differences in measured sound levels.

$$I \propto \frac{1}{r^2}$$

Figure 1. Inverse-square relationship used as the theoretical basis of sound propagation.

1.3. Recent Smartphone and Citizen-Science Noise Mapping

The rapid spread of smartphones has changed the practical possibilities of environmental noise monitoring. A conventional citywide campaign normally depends on a limited number of professional meters or predictive models, whereas smartphones can transform residents into distributed sensing participants. Picaut et al. documented how a smartphone-based crowd-sourced database can accumulate large volumes of georeferenced acoustic observations and make them available for spatial and temporal analysis [10]. Their work also emphasizes that a large database does not automatically guarantee reliable interpretation because metadata, device performance, anomalies, and calibration status must be considered when the data are reused. This observation is directly relevant to AudioHome because the value of a crowdsourced application depends not only on the number of recordings but also on how consistently those recordings are collected and interpreted.

Device variability remains one of the central methodological issues. Pődör and Szabó evaluated geo-tagged environmental noise measurements from different smartphones and applications and concluded that both hardware and software can materially influence the reported values [11]. Their findings support the use of standardized measurement procedures, repeated observations, controlled device settings, and, where possible, calibration against a reference instrument. In the context of AudioHome, this means that a future public deployment should store device model and calibration information as metadata rather than treating every smartphone reading as equally precise. Such metadata would allow the system to flag uncertain records, compare measurements from similar device families, and improve the credibility of aggregated noise maps.

Recent research has also moved beyond simple point measurement toward spatial decision support. Graziuso et al. used geo-crowdsourced sound-level data and spatial analysis to support planning around community facilities [12]. Boumchich, Picaut, and Bocher subsequently demonstrated how clustering methods can detect spatial events and organize large smartphone noise datasets [13]. These studies suggest that crowdsourced measurements become more useful when they are grouped by location, time, context, and statistical similarity. AudioHome already records decibel level, coordinates, and timestamps; therefore, the application contains the basic data structure needed for later clustering, hotspot detection, or density-based mapping without changing the core user workflow.

Citizen participation is not limited to data collection. Can et al. showed that participative noise mapping can also support dialogue between residents, researchers, and local authorities, especially when measurement activities are linked with collective interpretation and discussion [14]. Othman et al. similarly combined crowdsourcing applications with geographic information system techniques to associate measured noise levels with likely sound sources in different urban settings [15]. These approaches support the broader premise of the present study: a mobile application can be more than a digital sound meter. It can become a civic interface that helps users understand their acoustic environment, preserve evidence, identify recurring hotspots, and communicate concerns in a structured way.

The most recent work continues to emphasize quality control and policy usefulness. Alhazemi proposed sequential spatial and noise-level clustering to reduce the influence of outlier devices in mobile crowd-sensing platforms [16]. Siriba demonstrated in Nairobi that a custom crowdsourcing smartphone application can identify

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road-traffic noise hotspots for evidence-based urban regulation, while also noting the continuing importance of calibration and broader temporal sampling [17]. Together, these studies show a clear direction in the field: low-cost participatory sensing is increasingly feasible, but trustworthy urban noise intelligence requires transparent measurement protocols, validation rules, and a connection between citizen-generated data and institutional decision-making.

Table 3. Recent studies relevant to crowdsourced urban noise mapping

Study	Year	Main focus	Relevance to AudioHome
Picaut et al. [9]	2021	Large crowd-sourced smartphone noise database	Shows the value of georeferenced records and the need for metadata and quality control.
Pődör & Szabó [10]	2021	Accuracy of smartphone noise measurements	Supports calibration, device tracking, and standardized procedures.
Graziuso et al. [11]	2021	Geo-crowdsourced mapping for planning	Connects citizen measurements with spatial planning and mitigation.
Boumchich et al. [12]	2022	Spatial-event clustering of crowd-sourced records	Provides a pathway for hotspot and anomaly detection.
Can et al. [13]	2023	Citizen action and participatory diagnosis	Supports community involvement and co-design with authorities.
Othman et al. [14]	2024	Crowdsourcing, GIS, and source association	Shows how noise values can be interpreted with urban context and likely sources.
Alhazemi [16] / Siriba [17]	2025-2026	Quality filtering and policy-oriented mobile sensing	Reinforces outlier control, calibration, and evidence-based regulation.

1.4. Research Positioning and Objectives

Within this recent literature, the present study is positioned as a small-scale field evaluation of a locally developed mobile sensing and advocacy platform. The research does not claim to produce a complete strategic noise map of Jakarta. Instead, it evaluates whether the AudioHome workflow can capture meaningful spatial and temporal differences across selected urban contexts and whether the recorded information can be organized into forms that are useful for interpretation, archiving, and citizen reporting. This positioning is important because the four observation sites and the available sampling periods are exploratory rather than city-representative.

The study has four operational objectives. First, it examines whether AudioHome can consistently record sound level, location, and time as one structured observation. Second, it compares measurements from school-and-traffic, commercial, transport-corridor, and residential environments. Third, it evaluates application functions that transform raw readings into history records, trend summaries, saved locations, CSV data, and legal-advocacy outputs. Fourth, it interprets the strengths and limitations of this approach using recent literature on smartphone calibration, crowdsourced mapping, participatory sensing, and urban policy [10]-[17].

The novelty therefore lies in the integration of sensing and action. Many sound-level applications stop after displaying a current decibel value. AudioHome links the measurement with geographic context, temporal history, visual interpretation, and a pathway for formal reporting. For an urban community, that integrated workflow can reduce the distance between noticing a noisy condition and documenting it in a form that can support discussion with schools, neighborhood managers, or municipal authorities. The study evaluates that integrated concept while remaining cautious about the precision and representativeness of the current dataset.

2. Research Method

2.1. Research Approach and Observation Sites

The study uses a quantitative approach to compare environmental noise across four locations in Jakarta: Cempaka Putih Timur (Ahmad Yani Street), Cipinang Indah Raya near Cipinang Indah Mall, the Matraman Bus Corridor, and Kawasan Pulomas. The primary variables are noise level in decibels (dB), location, and observation time. Measurements were organized across daily periods so that spatial and temporal differences could be examined.

AudioHome served as the main data-collection instrument. The application automatically pairs decibel readings with location coordinates and timestamps. Measurements were taken at predetermined intervals, allowing data to be grouped by site and time period for comparison. Fixed observation points and repeated intervals were used to reduce inconsistency caused by short-term changes such as passing traffic or construction activity.

Table 1. Overview of observation locations and measured noise levels

Location	Area Type	Observation Period	Noise Level
Cempaka Putih Timur (Ahmad Yani St.)	School & traffic	12.00-01.00 PM, 26 Aug 2026	61 dB
Cipinang Indah Raya	Traffic & commercial	02.30-03.00 PM, 27 Aug 2026	72 dB
Matraman Bus Corridor	Traffic & commercial	01.30-02.00 PM, 26 Aug 2026	75 dB
Kawasan Pulomas	Residential	03.00-04.00 PM, 22 Aug 2026	58 dB

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The overview shows that the four locations represent different urban activity patterns, ranging from residential conditions to high-traffic and commercial corridors. The application standardizes collection by linking each measurement to place and time, providing a structured basis for later mapping and comparison.

2.2. Time Intervals and Noise-Mapping Workflow

At selected sites, measurements were divided into shorter intervals to capture variation within the day. The Cempaka Putih Timur dataset includes morning, midday, and evening periods, with 30-minute intervals used for finer temporal resolution. The resulting values ranged from 60 to 65 dB in the listed observations.

Table 2. Noise levels by time interval at Cempaka Putih Timur

Time	Noise Level (dB)
07.00-07.30	60
07.30-08.00	65
08.00-08.30	63
08.30-09.00	62
11.00-11.30	60
11.30-12.00	61
12.00-12.30	60
12.30-13.00	62
17.00-17.30	63
17.30-18.00	61
18.00-18.30	60
18.30-19.00	61

The noise-mapping workflow consists of five practical stages: noise measurement, location and time recording, data organization, noise mapping, and comparison and analysis. Data collection targeted early commuting activity, midday commercial and mixed traffic, and evening peak traffic. The structure is intended to account for local factors such as traffic flow, road design, and surrounding buildings.

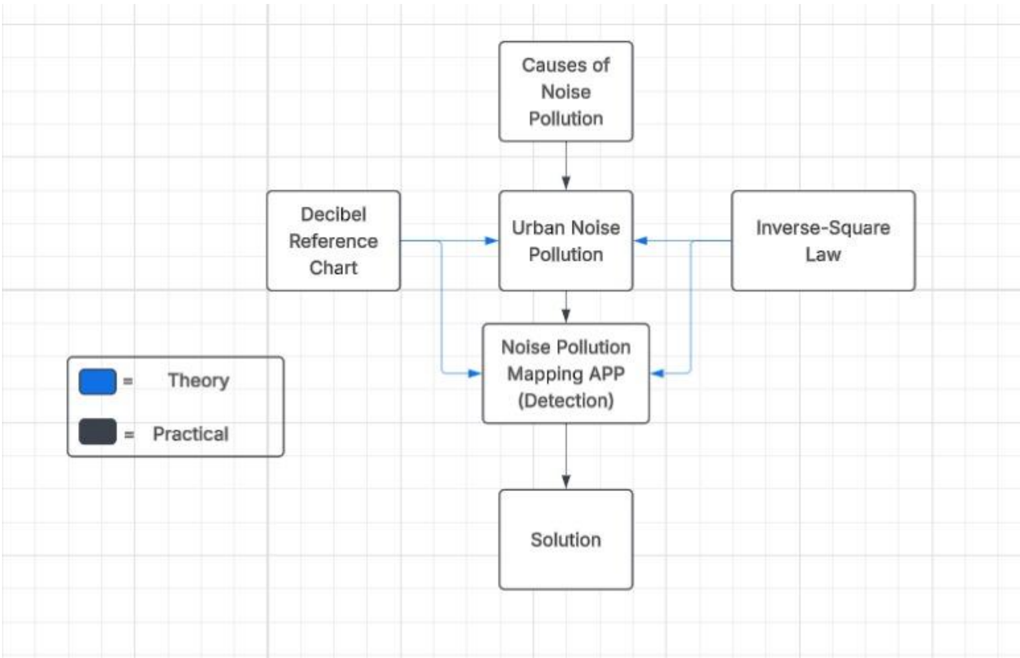

Figure 2. Practical and theoretical framework of the AudioHome noise-mapping system.

AudioHome also includes a user-reporting feature for perceived annoyance and possible noise sources such as traffic or construction. However, the source manuscript states that this feature was inactive during the initial data collection. Therefore, the empirical dataset used in this study consists of decibel readings, coordinates, and timestamps.

2.3. Measurement Reliability and Data-Quality Controls

Smartphone measurements are practical, but they are not automatically equivalent to certified sound-level-meter measurements. Differences in microphone sensitivity, automatic gain control, protective cases, device orientation, and software processing can produce systematic variation between phones [11]. For this reason, the present dataset is interpreted primarily as a comparative field dataset generated through one application workflow.

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The reported values are used to identify differences between the observed places and time intervals; they are not presented as a substitute for regulatory-grade acoustic certification.

The measurement procedure in the source study already reduces some forms of inconsistency by using predetermined observation points and organized time intervals. In an expanded implementation, reliability can be strengthened by recording the smartphone model, operating-system version, application version, calibration offset, microphone orientation, approximate distance from the dominant source, and environmental notes for each session. These fields would make it possible to separate changes in the acoustic environment from changes caused by the sensing device itself. Recent crowdsourced database research specifically recommends attention to calibration status, technical performance, and anomalous records when interpreting large public datasets [10].

A second control concerns temporal consistency. Urban noise is highly dynamic because traffic volume, vehicle type, construction, commercial activity, and weather can change over short periods. The Cempaka Putih Timur measurements illustrate this point: the recorded values vary between 60 and 65 dB across twelve half-hour intervals. Repeating observations at comparable times on different days would help determine whether a peak is a recurring feature or a one-time event. For future deployments, the application could prompt users to repeat a measurement when a value is unusually high or low relative to recent observations at the same location.

A third control concerns spatial consistency. GPS accuracy can vary between devices and urban settings, particularly around tall buildings or dense roadside environments. Because a change of only a short distance may alter exposure to a traffic lane, intersection, wall reflection, or localized sound source, spatial metadata should include both coordinates and an uncertainty estimate when available. Clustering methods such as those explored by Boumchich et al. and Alhazemi can later be used to group nearby valid measurements while reducing the influence of isolated spatial or acoustic outliers [13], [16].

Finally, the interpretation layer should preserve raw data. AudioHome already supports CSV export, which is a significant research advantage because users can inspect the underlying observations rather than relying only on graphical summaries. A robust version should retain the raw decibel series, summary indicators, timestamps, coordinates, device metadata, and any user-entered source labels. Separating raw data from derived classifications protects the audit trail and makes future reanalysis possible if legal thresholds, calibration models, or statistical methods are updated.

2.4. Descriptive Analysis Procedure

The analysis in this article is descriptive. For the four main observation sites, the measured site-level values are compared directly and interpreted in relation to the land-use context described in the source manuscript. The residential value at Kawasan Pulomas, 58 dB, is used as a simple local baseline for comparing the other three observations. The differences are expressed both in decibels and as approximate acoustic-intensity ratios using the logarithmic relationship between decibel difference and intensity. These ratios are included only to illustrate the physical meaning of a decibel difference; they should not be interpreted as a direct measure of perceived loudness.

For the Cempaka Putih Timur interval series, twelve half-hour observations are summarized using the arithmetic mean, median, minimum, maximum, and standard deviation. The sequence has a mean of 61.5 dB, a median of 61 dB, a minimum of 60 dB, a maximum of 65 dB, and a population standard deviation of approximately 1.5 dB. This relatively narrow spread suggests a stable but continuously elevated acoustic condition during the sampled periods, with a short morning peak. Because the dataset is small and non-random, no inferential statistical test is used to generalize the result to all days or to the broader district.

Interpretation also compares each observation with the functional characteristics of the location. Matraman and Cipinang Indah Raya are treated as traffic-and-commercial contexts; Cempaka Putih Timur represents a school-and-traffic context; and Kawasan Pulomas represents a residential context. This categorical comparison follows the structure of the source dataset and allows the discussion to ask whether the observed ranking is consistent with the expected intensity of human activity at each site.

The application screenshots are analyzed as functional evidence rather than as independent experimental results. The live screen, history view, saved-location feature, trends dashboard, and advocacy tool are reviewed to determine how the application transforms a measurement into a reusable record. User testimonies are treated as qualitative feedback on usability and perceived usefulness, not as a statistically representative satisfaction survey. This distinction keeps the claims aligned with the actual evidence available in the source manuscript.

2.5. Participatory and Data-Governance Considerations

Crowdsourced sensing introduces governance questions that become important if AudioHome is scaled beyond a small research group. Location and timestamp data can be sensitive because repeated records may reveal where a contributor spends time. A public version should therefore minimize personal identifiers, explain what data are collected, and allow users to contribute environmental observations without exposing unnecessary identity

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information. Aggregated public maps should prioritize area-level acoustic patterns rather than individual movement histories.

Data quality and privacy are closely related to public trust. Participants are more likely to contribute repeatedly when the application clearly explains how measurements are stored, how they will be used, and whether a report will be shared with authorities. Participatory noise-mapping research indicates that citizen engagement becomes more meaningful when contributors can see how their measurements contribute to a collective diagnosis rather than disappearing into an opaque database [14], [15]. AudioHome can support this by showing neighborhood summaries, explaining confidence levels, and distinguishing between preliminary community observations and validated regulatory measurements.

A policy-oriented workflow should also prevent automated advocacy from overstating the evidence. A generated complaint letter should summarize the observed location, time, recorded level, applicable threshold, number of repeated observations, and limitations of smartphone sensing. This preserves the usefulness of the advocacy feature while making clear that a citizen-generated record may trigger investigation rather than replace an official enforcement measurement. Such transparency would make the application more credible to both residents and local authorities.

3. Results and Discussion

3.1. Spatial and Temporal Noise Results

The measurements show clear differences among the four observation areas. The Matraman Bus Corridor produced the highest reported average at 75 dB, followed by Cipinang Indah Raya at 72 dB. Cempaka Putih Timur recorded 61 dB in the summarized observation and reached 65 dB during the 07.30-08.00 interval. Kawasan Pulomas, representing a residential environment, recorded the lowest summarized level at 58 dB.

These results indicate that locations characterized by heavy traffic and commercial activity generated higher measured sound levels than the residential location. The Cempaka Putih Timur interval data also demonstrate that the acoustic environment changes over time even at one fixed site. This supports the study rationale that short, isolated manual measurements may not represent the complete daily sound pattern.

The source manuscript relates these findings to the inverse-square law and to the immediate urban context. Distance from noise sources, traffic intensity, and the presence of surrounding buildings can influence the measured value. Accordingly, the application is designed not merely to store one reading, but to combine repeated measurements with their spatial and temporal context.

3.2. AudioHome Application Functions

AudioHome translates nearby recorded sound into decibel values and categorizes the local acoustic condition using thresholds programmed into the application. A live measurement screen displays the current dB level and recent statistics, while GPS support links the record to a location. The history function allows users to review previous measurements and revisit the measured area through map integration.

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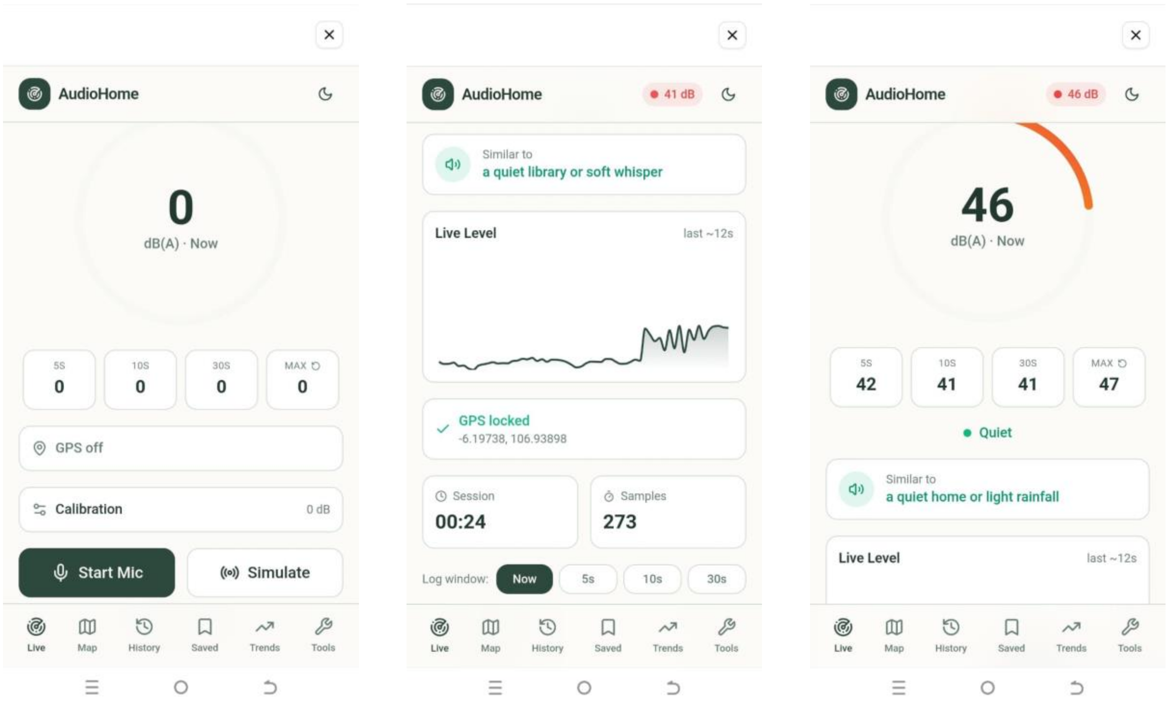

(a) Setup and calibration (b) Live logging (c) Current dB display

Figure 3. AudioHome measurement interfaces from the source manuscript: setup/calibration, live logging, and decibel measurement.

The interface example included in the source manuscript illustrates how a live session combines the current acoustic classification with a short-term level graph and GPS status. In the displayed example, the application shows a 41 dB reading, a locked GPS position, a 24-second session, and 273 samples. These values are interface examples shown in the manuscript screenshots rather than additional field-observation results.

The live interface also provides selectable logging windows and navigation to map, history, saved locations, trends, and tools. Earlier screenshots in the source manuscript show calibration and simulation controls as part of the same measurement workflow, supporting both direct recording and interface testing.

The application also provides trend visualization and category summaries to help users interpret changes over time. Figures 3-5 reproduce the complete set of AudioHome screenshots contained in the source manuscript, including setup and calibration, live measurement, history, saved locations, trends, time-of-day and category summaries, advocacy/legal-limit tools, and location checking. Raw measurement data can be exported in CSV format, which reduces the effort required to transfer observations into a separate research dataset.

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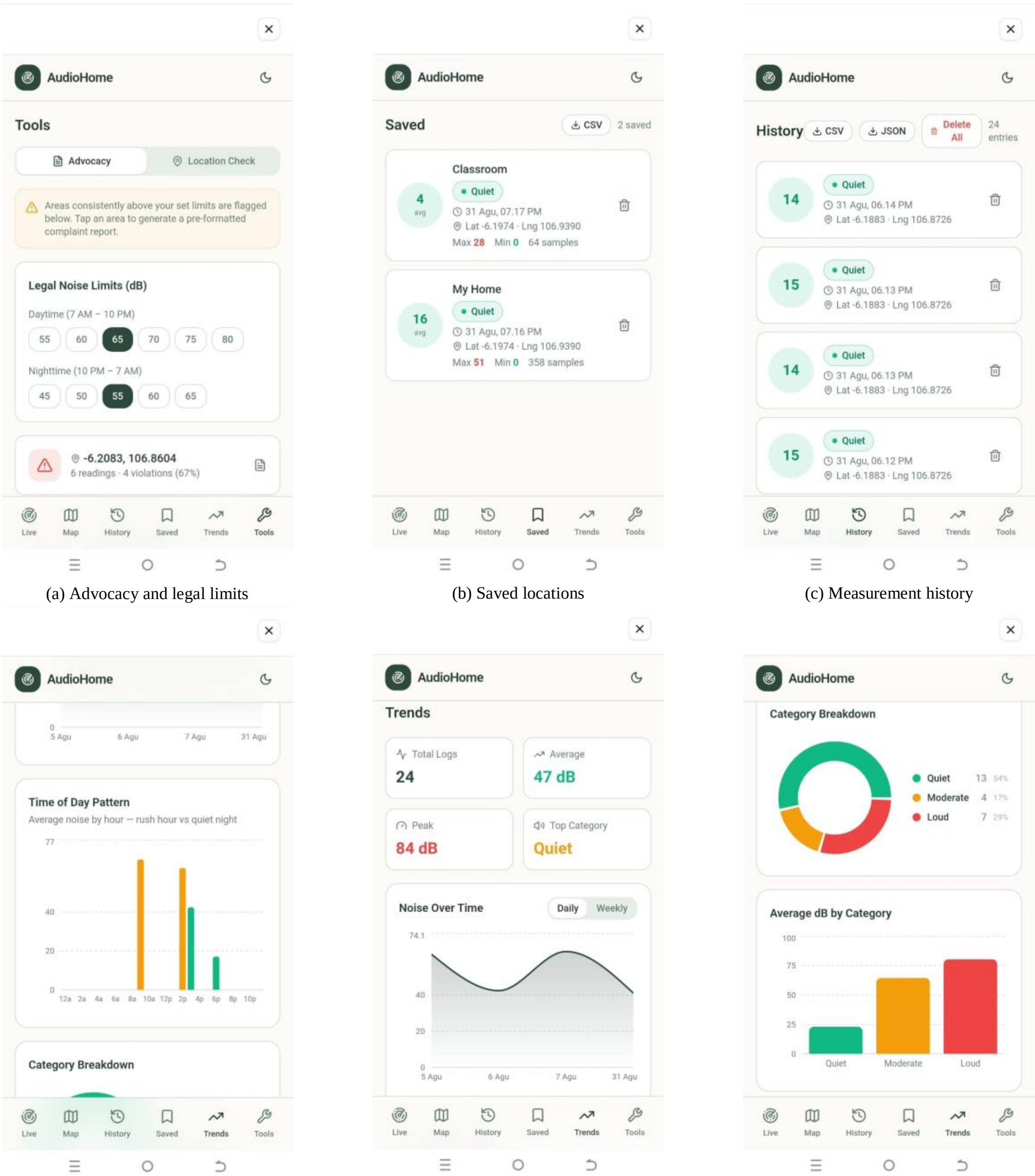

(a) Advocacy and legal limits (b) Saved locations (c) Measurement history

(d) Time-of-day pattern (e) Trend summary (f) Category breakdown

Figure 4. AudioHome tools, saved locations, history, time-of-day pattern, trend, and category-breakdown interfaces.

The trend-screen example shown in the source manuscript summarizes 24 total logs, an average of 47 dB, a peak of 84 dB, and Quiet as the top category. Because these values appear in an interface screenshot, they are treated as a demonstration of the analytical dashboard rather than as part of the four-location research table.

The accompanying history and saved-location screens demonstrate how individual records can be retained with dates, times, coordinates, categories, and measurement statistics, while frequently monitored places can be stored for later review. These functions help users move from a single measurement toward repeated observation of familiar locations and time patterns.

A further feature is the advocacy tool. When repeated high-intensity noise is identified, the application can generate a complaint letter that may be submitted to municipal or other relevant authorities. A location-check function also allows users to search an area and compare it with accepted noise conditions. Together, these functions extend the system from measurement toward practical community use.

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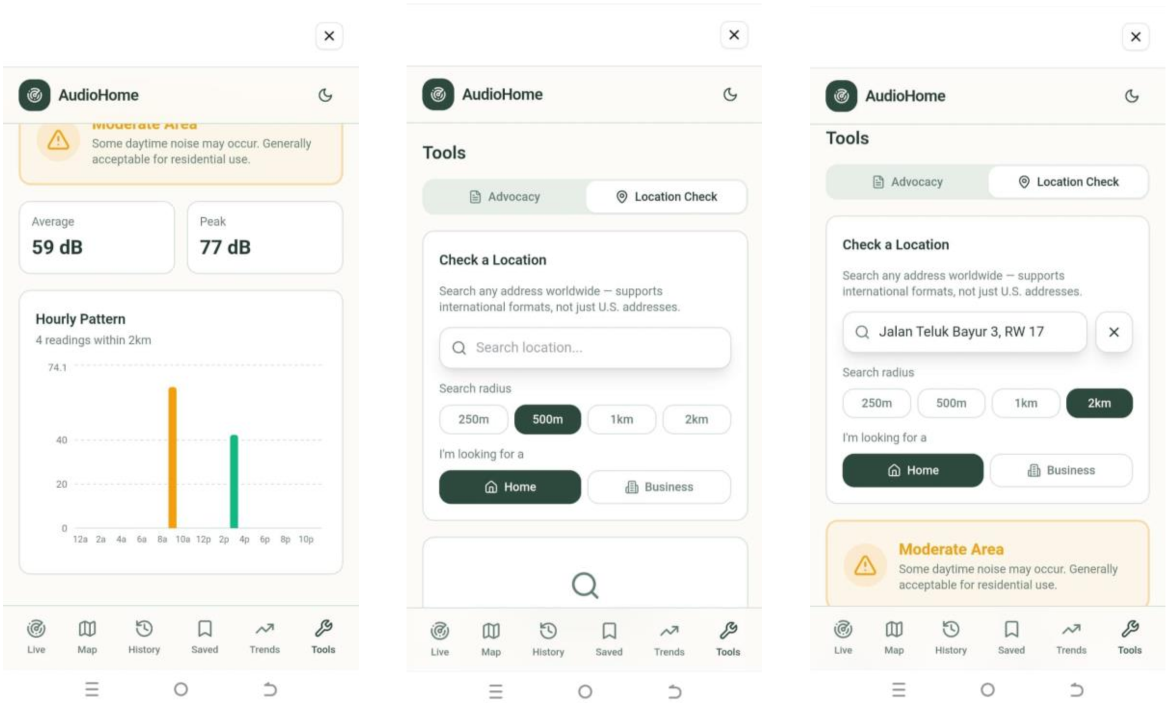

(a) Hourly pattern (b) Location search (c) Location-check result

Figure 5. AudioHome hourly pattern, location-search, and location-check interfaces from the source manuscript.

3.2.1. Complete Interface Documentation

Figures 3-5 retain the full visual documentation supplied in the source manuscript rather than selecting only representative screens. The first group shows the measurement workflow from an inactive microphone state through live logging and a current decibel display. The screens preserve the calibration control, simulation option, GPS status, session duration, sample count, short-term level graph, and acoustic category shown by the original application. Together, these interfaces demonstrate how a user can move from preparing a measurement to recording a location-aware observation without leaving the main AudioHome environment.

The second group documents how AudioHome stores and interprets previous observations. The tools view displays legal noise limits and an advocacy pathway; the saved-location and history views retain named places, dates, times, coordinates, categories, and measurement summaries; and the analytical views present time-of-day patterns, overall trends, peak and average values, and category breakdowns. Reproducing all six screens is important because the functionality is distributed across several pages of the application rather than concentrated in a single dashboard. The visual sequence therefore supports the article description of AudioHome as both a measurement tool and a lightweight data-management interface.

The final group documents the location-oriented functions. One screen summarizes an hourly pattern with average and peak values, while the remaining screens show the location-check tool before and after a search is performed. The source example includes a search radius, home-or-business selection, and a returned area classification. These screens extend the evidence beyond direct sound recording by showing how a user can review location context and compare an area with the application's stored criteria. When considered together with the history, trends, and advocacy interfaces, the complete image set illustrates the intended end-to-end workflow from sensing, to interpretation, to revisiting a place, and finally to communicating a potential noise concern.

3.3. User Feedback and Implications

User feedback in the source manuscript was generally positive. Respondents described the application as useful, interesting, and potentially beneficial for identifying quieter places. The more detailed evaluation highlighted live decibel logging, time-of-day trends, legal-limit alerts, advocacy functions, and CSV export as useful research features. The same evaluation also identified limitations, including the absence of continuous background recording while the phone is locked and the lack of detailed frequency-spectrum analysis for identifying specific noise sources.

The empirical results are consistent with both the earlier studies cited in the source manuscript and more recent participatory noise-mapping research. Higher traffic-related measurements support prior findings that road traffic is a dominant source of urban environmental noise [2], [7], while recent crowdsourced studies show that mobile

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sensing can reveal localized acoustic differences that conventional sparse monitoring may overlook [10], [13]-[15]. The observation that school and mixed-traffic locations can reach levels above the educational-zone threshold also reinforces concern about concentration and learning environments [3]-[5]. At the same time, the lower residential measurement at Kawasan Pulomas illustrates why localized and time-stamped data are necessary rather than assuming a single noise condition for the entire city.

From an applied perspective, the main contribution of AudioHome is the integration of measurement, location, time, visualization, data export, and advocacy into one mobile platform. The approach makes environmental sensing more accessible without requiring specialized sound-monitoring hardware for every observation. The current dataset remains limited to the four sites and the recorded intervals, so the results should be interpreted as a demonstration of the system and observed local patterns rather than as a complete noise map of Jakarta.

3.4. Extended Descriptive Interpretation

The four site measurements form a clear ranking: Matraman Bus Corridor at 75 dB, Cipinang Indah Raya at 72 dB, Cempaka Putih Timur at 61 dB in the overview table, and Kawasan Pulomas at 58 dB. The 17 dB difference between Matraman and Pulomas is substantial on the logarithmic decibel scale. Under the standard intensity relationship, a 17 dB increase corresponds to roughly fifty times the acoustic intensity, while the 14 dB difference between Cipinang and Pulomas corresponds to about twenty-five times the intensity. These calculations do not imply that people perceive the loudness as fifty or twenty-five times greater; they illustrate why relatively modest-looking numerical differences in dB can represent large physical differences in sound energy.

Table 4. Descriptive comparison of the four observation locations

Location	**Observed level**	**Difference from Pulomas**	**Approx. intensity ratio**	**Context interpretation**
Kawasan Pulomas	58 dB	0 dB	1.0×	Residential baseline in this dataset.
Cempaka Putih Timur	61 dB	+3 dB	2.0×	School and traffic exposure; persistent moderate elevation.
Cipinang Indah Raya	72 dB	+14 dB	25.1×	Commercial and traffic activity produces a much stronger acoustic environment.
Matraman Bus Corridor	75 dB	+17 dB	50.1×	Highest recorded site; consistent with dense transport and roadside activity.

The interval data from Cempaka Putih Timur provide a more detailed view than the single overview value. Across twelve observations, the mean is 61.5 dB and the values remain within a five-decibel range. The highest interval, 65 dB between 07.30 and 08.00, coincides with a plausible morning-mobility period, while most later observations remain around 60-63 dB. The pattern indicates that the location does not need an extreme peak to create a persistent acoustic burden; a relatively narrow band of elevated sound can continue across multiple parts of the day. This type of temporal pattern is precisely what periodic one-off monitoring may fail to describe.

The contrast between the four sites also demonstrates why citywide averages can be misleading. A single average for Jakarta would combine residential areas, school corridors, commercial streets, intersections, and transport corridors, potentially hiding the places where people experience repeated higher exposure. AudioHome instead supports a local record tied to coordinates and time. When many such records are accumulated, the same structure could be used to generate time-specific hotspot maps, compare weekday and weekend conditions, or identify whether mitigation changes a location over time.

3.5. Comparison with Recent Crowdsourced Noise-Mapping Research

The AudioHome concept is strongly aligned with the trajectory of recent smartphone noise research. Picaut et al. demonstrated the feasibility of maintaining a large crowd-sourced database in which each contribution contains acoustic and geographic information [10]. AudioHome follows the same general principle at a smaller scale by pairing decibel readings with coordinates and timestamps. The important lesson from that literature is that application design must anticipate later data analysis. Fields that appear optional during data collection—device type, calibration, source label, confidence, and measurement duration—become essential when thousands of heterogeneous observations must be compared.

Accuracy research also provides a necessary caution. Pődör and Szabó found that measurements can vary according to smartphone and software, meaning that an apparently precise numerical display should not be interpreted as proof of regulatory-grade accuracy [11]. The current AudioHome study can therefore be viewed as demonstrating workflow feasibility and relative spatial contrast rather than certifying exact legal exceedance at each site. A future validation stage should compare AudioHome measurements with a calibrated reference sound-level meter across several devices and sound environments and should store a device-specific correction value where appropriate.

The spatial-analysis literature suggests a clear technical development path. Graziuso et al. integrated geo-crowdsourced sound data with spatial density analysis for community-facility planning [12], while Boumchich et

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al. used clustering to identify spatial events in a crowd-sourced database [13]. These methods could be adapted so that AudioHome does not merely place individual points on a map. A server-side process could aggregate nearby readings into grid cells, calculate robust central values, flag cells with insufficient observations, and display separate layers by time of day. This would transform the current history-oriented map into an evidence layer that is more useful for neighborhood planning.

The participatory dimension is equally important. Can et al. report that citizen noise measurement can change how participants understand local sound environments and can create a basis for collective discussion [14]. Othman et al. show how crowdsourcing and GIS can be combined to associate noise levels with likely sources and support urban-planning recommendations [15]. AudioHome already contains a promising bridge from measurement to participation through saved locations, trends, and advocacy. Adding structured source categories—traffic, construction, commercial music, aircraft, community events, and other sources—would allow the platform to distinguish not only where noise is high, but also what contributors believe is producing it.

More recent mobile crowd-sensing research focuses on data screening. Alhazemi shows that full-population averaging can be distorted by spatial and acoustic outliers and proposes sequential clustering to remove misleading readings [16]. This is particularly relevant to a public application where devices may be positioned differently or may capture accidental local events. AudioHome could adopt a quality score based on calibration status, GPS uncertainty, measurement duration, distance to nearby records, and consistency with neighboring measurements. Records would remain visible in the raw archive, but only higher-confidence observations would contribute to official-looking hotspot summaries.

Siriba's 2026 Nairobi study provides a close policy parallel because it uses a custom crowdsourcing smartphone application to map road-traffic noise and argues that citizen-science measurements can help identify priority corridors for urban regulation [17]. The Nairobi experience also reinforces the need for calibration and expanded temporal coverage. For Jakarta, the same lesson suggests that AudioHome's strongest near-term role is as a screening and prioritization system: it can indicate where repeated high readings occur and where authorities or schools may wish to deploy professional instruments for confirmation.

3.6. Implications for Educational Environments and Urban Governance

The school-and-traffic context deserves particular attention because noise can interfere with speech communication and concentration even when it does not reach the highest values observed in commercial corridors. The Cempaka Putih Timur interval series remains around 60-65 dB, while the Indonesian environmental standard cited in the source manuscript specifies a 55 dBA limit for educational zones [5]. The earlier Jakarta school study also reported disruption to teaching and learning when traffic noise entered classrooms [4]. A school-facing version of AudioHome could therefore support periodic measurements at gates, classrooms near roads, courtyards, and drop-off areas, helping staff identify times when mitigation is most needed.

Possible mitigation does not need to rely on a single intervention. Repeated location-time data can help distinguish problems that are structural from those that are schedule-dependent. A consistently noisy roadside classroom may require acoustic barriers, improved windows, room reassignment, or vegetation and setback planning. A short morning peak may instead be addressed through traffic management, drop-off arrangements, enforcement against unnecessary horn use, or changes in the timing of outdoor activities. The value of the application is that interventions can be linked to a documented pattern rather than only to general complaints.

For local government, crowdsourced data can function as an early-warning layer. A municipal team cannot place a certified meter on every street, but a well-designed participatory system can reveal clusters of repeated complaints and high community measurements. Authorities can then prioritize professional verification at locations with strong, consistent evidence. This tiered model—community screening followed by official confirmation—respects the limitations of smartphone measurement while using public participation to increase spatial coverage.

The advocacy feature is especially distinctive because it translates a measurement into a communication artifact. Its effectiveness would increase if generated letters included a concise evidence table with date, time, coordinate, measured value, repeated-measurement count, applicable standard, and a statement that the measurement was collected by a smartphone-based community sensing tool. An automatically generated map snapshot and CSV attachment could provide additional context. This structure would make the output easier for a school manager or public official to evaluate without overstating the technical status of the data.

At a broader level, AudioHome can contribute to environmental literacy. Users who repeatedly record their surroundings begin to recognize that noise is spatial, temporal, and source-dependent rather than a fixed characteristic of a neighborhood. Participatory studies suggest that the act of measuring can itself increase awareness and discussion [14]. For students, this creates an educational opportunity that connects physics, data science, geography, environmental health, and civic participation in one practical project.

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3.7. Limitations and Future Development

The principal limitation of the present study is the size and structure of the dataset. Four main locations are sufficient to demonstrate differences, but they cannot represent the full spatial diversity of Jakarta. The observation dates and times are also uneven across locations, which means that differences may partly reflect temporal conditions rather than land-use type alone. Future studies should use a balanced sampling design with repeated weekday and weekend sessions at the same morning, midday, afternoon, evening, and night periods.

A second limitation is the absence of a documented calibration study against a professional reference instrument. Without such validation, the reported readings should be interpreted as application-based environmental observations rather than certified regulatory measurements. A future experiment should place several smartphone models beside a calibrated Class 1 or Class 2 sound-level meter, expose them to a range of stable and variable sound conditions, estimate device-specific offsets, and test whether those offsets remain stable in field use. The recent smartphone accuracy literature makes this a priority for any system intended to support formal decision-making [10], [11], [16].

A third limitation concerns source identification. The current dataset primarily contains decibel level, location, and time. It does not systematically label whether the dominant sound came from motorcycles, buses, horns, construction, commercial activity, aircraft, people, or other sources. Adding a simple source-classification prompt would make the map more actionable because different sources require different mitigation strategies. Future versions could combine user labels with on-device acoustic classification, provided that privacy is protected and raw speech content is not retained.

The current user feedback is also exploratory. The testimonies demonstrate perceived usefulness and suggest desired features such as background measurement, spectral analysis, and map integration, but the number and recruitment method of respondents do not support general claims about usability. A future usability study should define participant groups, standardized tasks, completion times, error rates, perceived ease of use, and willingness to contribute repeatedly. This would help distinguish technical performance from user acceptance.

Finally, the application should evolve from displaying individual measurements toward communicating uncertainty and evidence strength. A future map could distinguish single observations from repeated clusters, display confidence categories, show the number of contributors behind each cell, and separate uncalibrated community data from validated measurements. These changes would align AudioHome with the strongest lessons of recent crowdsourcing research: broad participation is valuable, but responsible interpretation requires calibration, filtering, metadata, repeat observations, and transparent limits [10]-[17].

3.8. Proposed Scalable AudioHome Architecture

Scaling AudioHome from an exploratory application into a city-support platform requires a layered architecture that separates sensing, validation, storage, analysis, and communication. At the sensing layer, the smartphone should collect the minimum acoustic indicator required by the study together with timestamp, coordinates, measurement duration, device model, calibration offset, and optional source labels. The interface should continue to remain simple for contributors, because a crowdsourcing platform loses value if technically correct data entry requires excessive effort. The more complex quality checks can therefore occur automatically in the background after the user completes a measurement.

At the validation layer, each uploaded record could receive a quality score before it contributes to public summaries. Basic checks would include whether the GPS position is plausible, whether the measurement duration reaches a defined minimum, whether the reported value falls within an expected technical range, and whether the device has a known calibration profile. Spatial consistency can then be assessed by comparing the record with nearby measurements collected within a similar time window. Research on clustering and mobile crowd sensing indicates that this type of screening is important because outlier devices or poorly positioned observations can distort an area-level estimate [13], [16]. A quality score would not need to delete low-confidence data; it could simply prevent those records from dominating the map.

The storage layer should preserve both raw and processed information. Raw records are necessary for auditability, while processed tables can support faster map rendering and trend analysis. A practical structure would maintain an immutable measurement identifier, contributor anonymity token, coordinates, time, device metadata, decibel statistics, source category, calibration data, and quality flags. Aggregated products could then be generated by grid cell, road segment, school zone, neighborhood, or time period. This approach follows the broader lesson from recent crowd-sourced noise databases that the long-term scientific value of a platform depends on well-organized metadata as much as on the number of measurements [10].

The analysis layer could produce several outputs from the same dataset. A public user may only need a simple quiet-to-loud map and a recent trend line. A school may need comparisons between classroom periods, arrival times, dismissal times, and weekend baselines. A municipal user may need repeated exceedance clusters, source

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categories, confidence scores, and downloadable evidence packages. Separating these analytical views prevents the application from overwhelming ordinary contributors while still making the platform useful for more technical users. It also allows future analytical methods to be added without redesigning the basic measurement interface.

The communication layer should distinguish awareness, screening, and enforcement. Community maps can be presented as participatory observations, while locations that meet a predefined repetition and confidence threshold can be marked as candidates for professional verification. The advocacy generator can then reference the history of repeated measurements rather than a single isolated value. This architecture would make the relationship between citizen sensing and government action more defensible: citizens help identify where attention is needed, and authorities retain responsibility for formal verification and enforcement. Participatory studies indicate that this transparent connection between measurement and decision-making is central to sustaining community engagement [14], [15], [17].

3.9. Recommended Future Evaluation Protocol

A stronger follow-up study should use a staged validation protocol. The first stage would be laboratory or controlled-field calibration using several common smartphone models placed beside a reference sound-level meter. Stable sound conditions at multiple levels could be used to estimate device-specific offsets and determine whether those offsets remain consistent across repeated trials. The second stage would test the same devices outdoors under traffic, commercial, school, and residential conditions. This would directly address the concern raised in smartphone-accuracy research that laboratory agreement does not necessarily guarantee equivalent performance in heterogeneous real-world environments [11].

The third stage should expand spatial and temporal sampling. Instead of one principal observation per site, each location could be measured on multiple weekdays and weekends, with fixed sessions in the morning, midday, afternoon, evening, and night. At least several sites should be selected within each land-use category so that differences between categories are not driven by one street or one exceptional event. A repeated-measures design would also allow the study to estimate within-site variability, between-site variability, and the stability of identified hotspots. The same protocol could be implemented gradually across schools and neighborhoods to build a more representative Jakarta dataset.

The fourth stage should evaluate user participation. Contributors could be assigned realistic tasks such as recording a location, saving a site, exporting a CSV file, interpreting a trend, and generating an advocacy report. Completion time, task errors, comprehension, perceived usefulness, and willingness to contribute again could be recorded. A separate group of teachers, community leaders, or local-government users could evaluate whether the resulting maps and reports contain enough information to support a decision. This would provide evidence about the full system, not only about microphone performance.

Finally, the expanded study should define success criteria before data collection begins. Technical criteria could include agreement with a reference meter, GPS completeness, proportion of valid records, and repeatability. Analytical criteria could include the ability to reproduce known spatial differences and identify stable hotspots. Participation criteria could include successful task completion and repeated contribution rates. Policy criteria could include whether officials can understand the evidence package and decide when professional verification is warranted. Using explicit criteria would allow AudioHome to progress from a promising prototype toward a transparent, reproducible environmental sensing platform.

3.10. Practical Implementation Roadmap

A practical implementation roadmap can be organized into three successive levels. The first level is a controlled school-and-community pilot in which a limited number of calibrated or cross-checked smartphones are used at predefined sites. The purpose of this stage is to test data consistency, refine the user interface, verify the CSV structure, and determine whether the advocacy output is understandable to non-technical users. Because the current study already demonstrates the core measurement and history workflow, this first stage can focus on reliability rather than adding many new interface features.

The second level is a multi-site participatory deployment. Schools, residential communities, and selected transport corridors could contribute repeated measurements under a common protocol. At this stage, the server should automatically apply validation rules, generate grid-based summaries, and display the number of valid observations behind each mapped value. Contributors should also be able to classify likely noise sources and indicate whether the sound was continuous, intermittent, or event-based. These additions would make it easier to distinguish a persistent hotspot from a temporary event and would improve the usefulness of the map for planning.

The third level is institutional integration. Once the platform has sufficient validated data, local authorities could receive dashboards that prioritize locations according to repeated high measurements, confidence score, land-use sensitivity, and number of community reports. Schools could receive periodic summaries for educational zones, while residents could continue to view simplified public maps. Professional acoustic measurements would

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still be required for formal enforcement, but AudioHome could substantially improve where and when those resources are deployed. In this model, crowdsourcing does not replace official monitoring; it increases coverage, improves prioritization, and creates a transparent evidence trail between community observation and formal follow-up.

4. Conclusion

This research demonstrates that AudioHome can organize smartphone-based environmental noise observations into a practical workflow that links sound level, location, time, history, visualization, data export, and advocacy. The four Jakarta observation sites show a clear contextual gradient, with the highest values in traffic and commercial corridors and the lowest value in the residential area. The Cempaka Putih Timur interval series further shows that a location can maintain a relatively stable elevated level across different parts of the day rather than being defined only by isolated peaks. These findings answer the study objective at an exploratory level: localized, time-stamped mobile measurements can reveal meaningful spatial and temporal differences that are difficult to see through occasional manual sampling alone.

The contribution of AudioHome is not limited to sensing. By retaining history, displaying trends, saving locations, exporting structured data, and generating an advocacy document, the application connects environmental observation with civic action. Recent research from 2021-2026 supports this direction while also clarifying the conditions required for responsible use: smartphone and software variability must be acknowledged, calibration should be documented, spatial and acoustic outliers should be controlled, sampling should be repeated, and public maps should communicate data confidence [10]-[17]. Accordingly, AudioHome is best positioned as a low-cost screening, awareness, and prioritization tool that can guide where more formal acoustic assessment is needed.

Future development should therefore focus on reference-meter calibration, device metadata, balanced sampling schedules, source classification, privacy-preserving aggregation, confidence scoring, and larger participatory trials across Jakarta. With these improvements, crowdsourced sensing could complement official monitoring by increasing spatial coverage and involving schools and communities directly in the diagnosis of their acoustic environment. The long-term value of the platform lies in transforming many small, transparent, well-documented observations into evidence that can support quieter learning environments, healthier neighborhoods, and more responsive urban noise management.

In operational terms, the most appropriate next step is not immediate citywide deployment but a controlled expansion in which the same protocol is repeated across more sites and devices. A larger dataset should preserve the present strengths of AudioHome—simple measurement, geolocation, time history, visual trends, CSV export, and advocacy—while adding calibration records, confidence indicators, and explicit source categories. The system should also separate community screening from regulatory confirmation so that users understand what a smartphone observation can and cannot establish. This distinction is essential for responsible communication with schools and municipal agencies. If repeated high-confidence observations are used to prioritize professional verification, the application can reduce the cost of finding problem locations without claiming to replace certified acoustic instruments. The resulting workflow would connect citizen science, environmental education, and public administration in a practical sequence: communities identify recurring acoustic concerns, the platform organizes and validates the evidence, and institutions decide where formal assessment or mitigation is required. Such a model is consistent with recent participatory and policy-oriented noise-mapping studies and provides a realistic pathway for developing AudioHome from a research prototype into a sustainable urban environmental information system [14]-[17].

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