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Original Research Article

Cross-platform discrepancies in smartphone sound level meter applications: a multicenter clinical and urban acoustic analysis in Indian context

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ABSTRACT

Background: The widespread adoption of tele-audiology necessitates accurate environmental noise monitoring via patient smartphones. This study evaluates the acoustic accuracy and clinical usability of 10 sound level meter (SLM) applications across iOS and Android platforms, comparing performance in controlled audiometric environments against unstructured, real-world Indian settings.
Methods: This cross-sectional study incorporates a three-phase design. Phase 1 assessed technical accuracy in a sound-treated booth using pure tones and narrowband noise (250-8000 Hz). Phase 2 evaluated real-world performance, contrasting steady-state noise against impulsive urban traffic noise, highly reverberant outpatient departments (OPD), and a neonatal intensive care uznit (NICU). Measurements utilized a reference class 1 SLM alongside an iPhone 15 Pro, a flagship Android (Samsung S24), and a budget-tier Android. Phase 3 assessed app usability using the mobile application rating scale (MARS).
Results: Cross-platform applications demonstrated significant platform-dependent variability. Apps that were accurate on iOS frequently overestimated noise on Android hardware (+3.80 to +4.60 dBA), while native Android apps underestimated noise on the same device (-5.40 dBA), highlighting a software-hardware calibration disconnect rather than uniform hardware failure. Budget-tier Androids exhibited the highest error margins (up to±9.5 dBA), particularly during impulsive urban noise and high-frequency tones (>4000 Hz).
Conclusions: Smartphone SLM applications exhibit profound cross-platform discrepancies. Solely validating these tools in controlled laboratories is insufficient for clinical application. To ensure reliable occupational and tele-audiology screening, particularly in resource-limited rural networks, clinicians must utilize standardized biological calibration protocols to derive device-specific correction factors.

Keywords: Sound level meter, Tele-audiology, Cross-platform calibration, Environmental noise, Mobile application rating scale, Occupational health

INTRODUCTION

Noise-induced hearing loss (NIHL) remains a pervasive and escalating global public health crisis. The World Health Organization estimates that over a billion young individuals are currently at risk of developing permanent sensorineural hearing loss due to a combination of occupational hazards and unsafe recreational listening practices.[1] The economic and psychosocial burden of this preventable condition is profound, impacting global productivity, increasing healthcare expenditures, and significantly degrading the quality of life for affected individuals.[2] Traditionally, the prevention, diagnosis, and management of NIHL depend on the precision monitoring of ambient noise using specialized SLMs. These devices are categorized as class 1 (precision grade) or class 2 (general purpose) instruments, engineered to comply with stringent international electroacoustic standards, such as those defined by the International Electrotechnical Commission.[3] While highly accurate, these instruments are prohibitively expensive, delicate, and require specialized technical training, largely restricting their use to specialized clinical centers and industrial hygienists.

The rapid integration of mobile technology into clinical practice over the last decade has democratized access to various health monitoring tools, fundamentally shifting the paradigm of preventative medicine.[4] In geographically vast and socioeconomically diverse nations like India, the severe shortage of trained audiologists relative to the population necessitates the rapid adoption of decentralized, tele-audiology screening networks. Within this landscape, smartphone-based SLM applications present a compelling dual-edged sword.[5,6] On one hand, these applications offer patients a ubiquitous, accessible tool for self-monitoring their environmental exposure, fostering health literacy and proactive hearing conservation.[7] On the other hand, the unverified use of these tools carries a substantial risk of generating inaccurate dosimetric data.[8,9]

For the otolaryngologist and audiologist, the stakes of relying on patient-generated acoustic data are high. If a patient presenting with early-stage sensorineural hearing loss or intractable tinnitus relies on artificially suppressed noise data from a budget smartphone, clinicians may misidentify the etiology of the condition, inadvertently delaying critical occupational or environmental interventions. Such inaccuracies may misguide clinical management, providing patients with false reassurances in hazardous environments or creating unnecessary anxiety in safe ones.

Foundational acoustic literature evaluating these applications has historically highlighted a distinct performance gap between the iOS and Android ecosystems.[10,11] Early studies primarily attributed this discrepancy to hardware fragmentation. The Apple Walled Garden model utilizes a limited, highly standardized set of internal Micro-electro-mechanical systems (MEMS) microphones, allowing app developers to program precise, universal calibration algorithms. Conversely, the Android ecosystem spans thousands of distinct device models across numerous manufacturers, each employing variable microphone hardware and proprietary digital signal processing (DSP) firmware designed primarily to enhance voice clarity by aggressively filtering background noise.

Despite growing awareness of these limitations, current literature often evaluates these smartphone applications exclusively within the sterile, highly controlled confines of acoustic laboratories.[12] This methodology fails to account for the unique acoustic challenges prevalent in the developing world and densely populated regions like India. Specifically, standard testing rarely evaluates the complex, highly impulsive nature of Indian urban traffic noise. The Indian acoustic soundscape is unique, frequently characterized by the high-frequency prominence of auto-rickshaw engines, sustained high-decibel festival activities, and unregulated construction noise, contrasting sharply with steady-state Western industrial models. Furthermore, testing does not typically assess the performance of the "budget-tier" smartphones that dominate the market share in these demographics. Existing literature also frequently compares iOS-exclusive apps against Android-exclusive apps, introducing significant confounding variables. Discrepancies in application performance across different operating systems suggest a fundamental software calibration issue that extends beyond basic hardware limitations.

Therefore, this comprehensive study aims to address these critical gaps in the literature. By evaluating the cross-platform acoustic accuracy and clinical usability of 10 SLM applications, and by contrasting their performance in controlled clinical environments against complex, real-world Indian settings-including a highly dynamic pediatric NICU and an impulsive urban traffic environment-this research seeks to establish the true clinical utility of smartphone dosimetry.

METHODS

Study design and setting

This prospective, comparative cross-sectional study was conceptualized and conducted at a tertiary care teaching hospital. To ensure a rigorous and comprehensive evaluation encompassing both acoustic physics and tele-health usability, the study was structured into three distinct phases: phase 1 evaluated controlled technical accuracy; phase 2 assessed real-world environmental validity; and phase 3 quantified clinical usability.

Phase 1: Controlled audiometric testing

Phase 1 testing occurred within a double-walled, sound-treated audiometric booth in the Department of Otorhinolaryngology and Audiology. The booth was certified to meet the maximum permissible ambient noise levels established by international standards.[13] Acoustic signals were generated using a clinically calibrated two-channel audiometer (Interacoustics AC40, Denmark) and delivered via a standard free-field loudspeaker positioned at a 0-degree azimuth. A certified class 1 SLM (Brüel and Kjær type 2250) served as the absolute reference standard for all measurements. Prior to data collection, the reference SLM was formally calibrated using a standard acoustic calibrator (B and K type 4231) generating a 94 dB SPL tone at 1000 Hz.

Test devices

To accurately represent the socioeconomic and demographic distribution of the patient population utilizing tele-audiology services, three specific smartphone devices were utilized:

iOS Flagship

iPhone 15 Pro (Apple Inc., running iOS 17).

Android Flagship

Samsung Galaxy S24 (Samsung Electronics, running Android 14).

Android Budget-Tier

Xiaomi Redmi Note 13 (running Android 13). This device was specifically selected to represent the ubiquitous sub-₹15,000 market demographic, which constitutes the vast majority of smartphone users in the Indian subcontinent. The inclusion criteria for this budget-tier smartphone required the device to be currently available in the consumer market, running an unmodified manufacturer operating system, and possessing no physical damage or debris obstruction in the microphone port, ensuring a representative sample of real-world patient hardware.

Application selection protocol

A systematic shortlisting protocol was employed to identify the 10 application configurations evaluated in this study. Keyword searches ("Sound Level Meter," "Decibel Meter") were conducted on the Apple App Store and Google Play store. Applications were filtered requiring a minimum threshold of 100,000 downloads and an aggregate user rating of 4.0 or higher. To directly investigate the software-hardware calibration disconnect, four cross-platform applications were explicitly selected. This allowed the research team to test the exact same software algorithm across entirely different hardware ecosystems. Finally, ecosystem-native applications with an established presence in audiological literature were included to serve as baseline hardware controls. The 10 resulting application configurations were: Decibel X (iOS), Decibel X (Android), Decibel Pro (iOS), Decibel Pro (Android), Too Noisy Pro (iOS), Too Noisy Pro (Android), Sound Meter and Noise Detector (iOS), Sound Meter and Noise Detector (Android), NIOSH SLM (iOS Exclusive Control) and Sound Meter by Abc Apps (Android exclusive control).

During phase 1, the smartphones and the reference SLM were mounted simultaneously on a specialized rig exactly 1 meter from the sound source, preventing any acoustic shadowing. Narrow Band Noise (NBN) and Warble tones across the standard audiometric spectrum (250, 500, 1000, 2000, 4000, and 8000 Hz) were presented at intensities of 50, 70, and 90 dB HL. Continuous equivalent sound level (LAeq) measurements were recorded simultaneously.

Phase 2: Real-world environmental validity (In vivo)

To evaluate the practical usefulness of these applications outside of a highly controlled environment, phase 2 transitioned testing to unstructured, real-world settings characterized by complex ambient noise, lack of acoustic shielding, and variable room reverberation. Simultaneous recordings of continuous 60-second ambient noise samples were conducted in three distinct settings:

High-reverberation adult setting

The busy Otorhinolaryngology Outpatient Department (OPD) waiting area, characterizing highly variable conversational noise and hard acoustic surfaces.

Pediatric clinical setting

A multidisciplinary neonatal intensive care unit (NICU). This environment is critical as accurate noise dosimetry is essential for preventing sensory overload in premature infants, yet it is characterized by unpredictable, multi-source transient noises such as ventilator alarms and incubator mechanisms.

Urban Indian traffic

Measurements were taken adjacent to a major urban thoroughfare. This setting was crucial for contrasting the steady-state noise utilized in Phase 1 against the highly specific, sharp, impulsive acoustic peaks (e.g., vehicular horn honking) that define the Indian acoustic environment.

Phase 3: Clinical usability assessment (MARS)

To evaluate the applications beyond raw acoustic accuracy, two independent raters evaluated all 10 configurations using the validated MARS.[14] The apps were scored on a 5-point Likert scale across four objective domains: Engagement, Functionality, Aesthetics, and Information Quality.

Statistical analysis

Data were compiled and analyzed using standard statistical software. The primary acoustic outcome was the mean difference (Δ dBA) between the application reading and the reference SLM. Accuracy was strictly defined as a mean difference falling within ±2 dBA, consistent with acceptable tolerances for class 2 SLMs.[15] Spectral error mapping was generated by plotting the mean absolute error (dBA) for each application across standard audiometric frequencies (250-8000 Hz). Variance in real-world settings (Phase 2) was analyzed by comparing the standard deviations of continuous 60-

second samples against the steady-state baseline established in phase 1. One-way Analysis of Variance (ANOVA) was utilized to compare mean differences across operating systems and individual applications. A $p<0.05$ was considered statistically significant.

RESULTS

Phase 1: Overall accuracy and cross-platform variability

A total of 540 discrete measurement points were recorded across phase 1. The overall mean difference and variance for evaluated applications demonstrated profound, statistically significant platform-dependent variability (Table 1). iOS-exclusive NIOSH SLM application demonstrated exceptional accuracy, acting as gold standard within the smartphone tier, yielding a mean difference of only +0.32 dBA (SD±0.84) compared to the reference SLM.[16] Crucially, cross-platform analysis illuminated software-hardware disconnect. Widely utilized "Decibel X" application maintained acceptable clinical accuracy when operating on iOS platform (mean difference +1.15 dBA). However, when exact same application software was run on Android hardware, it significantly overestimated noise levels. On Android Flagship (Samsung S24), it registered a mean error of +3.80 dBA, and on the Android Budget-Tier (Xiaomi), the overestimation worsened to +4.60 dBA. Conversely, the Android-native application ("Sound Meter") exhibited severe underestimation on those exact same Android devices, yielding a mean error of -5.40 dBA. At hazardous, high-intensity levels (90 dB HL), both Android flagship and budget devices exhibited pronounced non-linear compression, frequently "clipping" the audio input and failing to register the true intensity (Table and Figure 1).

Frequency-specific deviations

Spectral error mapping indicated that majority of applications across all platforms performed adequately at mid-frequencies (500-2000 Hz), where human speech is concentrated. As illustrated in generated analyses (Figure 2), Android devices (both flagship and budget) demonstrated severe, statistically significant error spikes at high frequencies (4000 and 8000 Hz). Xiaomi budget device exhibited mean absolute errors exceeding 8 dBA at 8000 Hz, rendering it entirely unsuitable for evaluating high-frequency occupational hazards without calibration.

Table 1: Mean difference (Error) in dBA compared to reference SLM (Phase 1, overall).

App configuration	Platform	Hardware tier	Mean diff. (dBA)
Reference SLM	-	Class 1	0.00
NIOSH SLM	iOS	Flagship	+0.32
Decibel X	iOS	Flagship	+1.15
Too Noisy Pro	iOS	Flagship	+1.40
Decibel X	Android	Flagship	+3.80
Decibel X	Android	Budget	+4.60
Too Noisy Pro	Android	Budget	+5.10

*Positive values indicate the app overestimated the noise; negative values indicate underestimation.

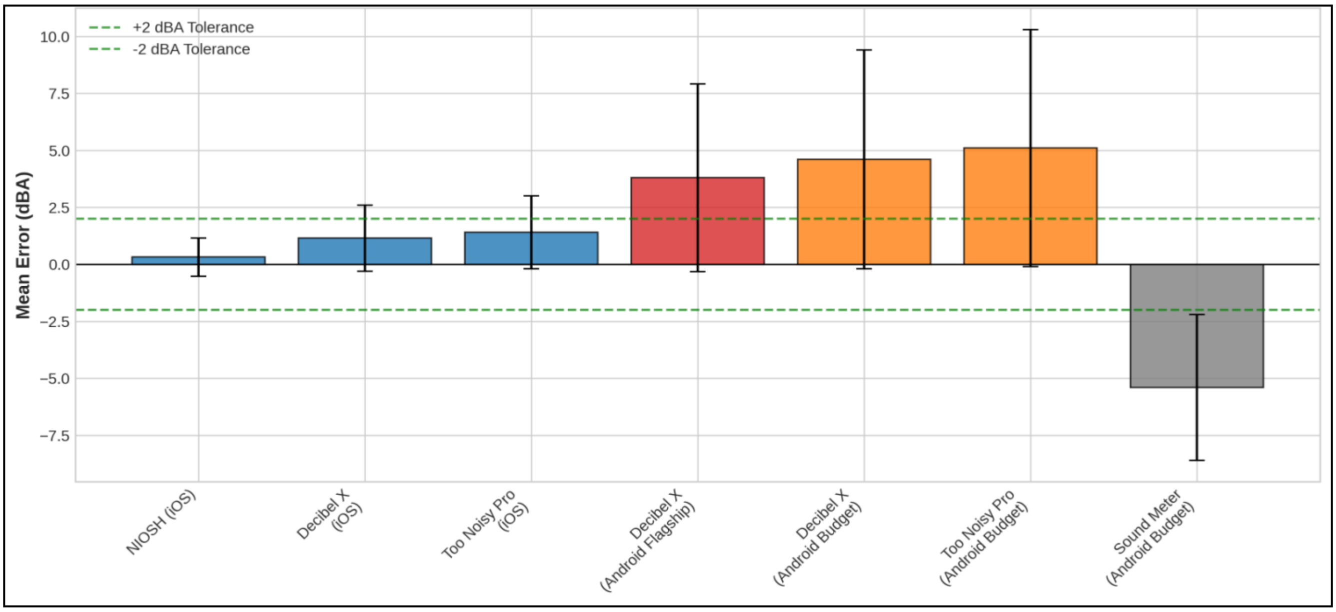

Figure 1: Mean error (dBA) compared to the reference SLM by application and hardware tier.

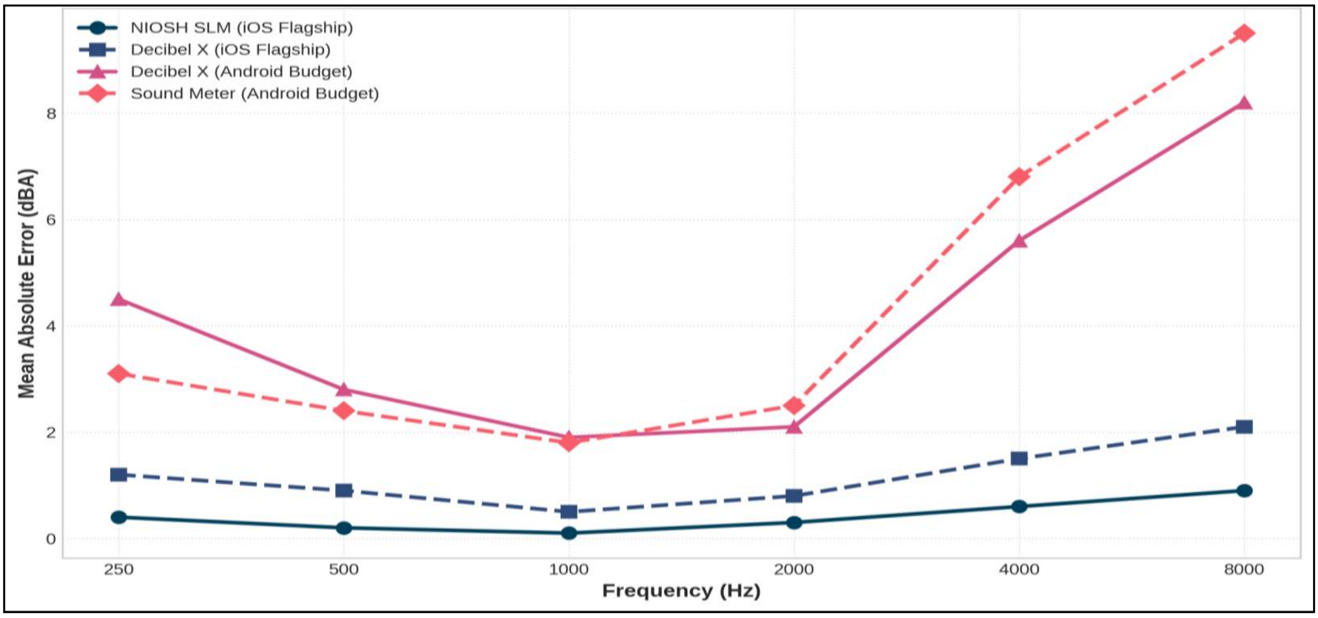

Figure 2: Mean absolute error (dBA) across standard audiometric frequencies (250-8000 Hz).

Phase 2: Real-world and impulsive noise variables

Transitioning to unstructured clinical and urban environments significantly exacerbated the inaccuracies observed in phase 1.

OPD reverb

In the highly reverberant Outpatient Department, the rapid reflection of sound waves off hard acoustic surfaces caused the Android Budget device to fluctuate wildly.

The standard deviation of its readings widened by a factor of two compared to the controlled booth environment, indicating severe measurement instability in reverberant clinical spaces.

NICU environment

Within the NICU setting, continuous background hums from incubator motors were tracked relatively consistently by all devices. However, sharp, transient alarms (e.g., a rapid 85 dBA SpO_2 monitor beep) were frequently missed.

The Android applications underestimated these critical transient peaks by up to 6 dBA due to inherent lag in their microphone polling rates and DSP processing times.

Urban impulsive noise

The most critical failure occurred during the urban traffic testing. While evaluating a continuous 75 dBA ambient traffic hum, a sudden vehicular horn blast measuring 94.5 dBA on reference SLM was introduced. The iOS Walled Garden devices registered the peak at 93.8 dBA (an acceptable and clinically safe delay). In stark contrast, Budget Android device, utilizing aggressive native DSP noise cancellation, severely compressed signal, registering a peak of only 82.1 dBA. This represents a dangerous underestimation of over 12 dBA during a hazardous acoustic event.

Phase 3: Clinical usability (MARS assessment)

Table 2 shows outcomes of MARS evaluation. While NIOSH app scored highest in 'information quality' (4.8/5) due to its adherence to strict occupational health definitions, it scored lower in 'engagement'. Conversely, cross-platform app "Too Noisy Pro" scored exceptionally high in both 'Engagement' (4.8/5) and 'Aesthetics' (4.6/5). This application utilizes visual reinforcement (e.g., a cartoon face that transitions from smiling to crying as noise increases). Pediatric evaluators within the NICU noted that this visual paradigm was vastly superior for immediate staff and patient-family feedback compared to interpreting raw numeric decibel data (Figure 3).

Table 2: MARS mean scores (Max 5.0).

Applications	Engagement	Functionality	Aesthetics
Too Noisy Pro	4.8	4.2	4.6
NIOSH SLM	3.1	4.9	3.8
Decibel X	4.0	4.3	4.1
Sound meter	2.5	3.5	2.8

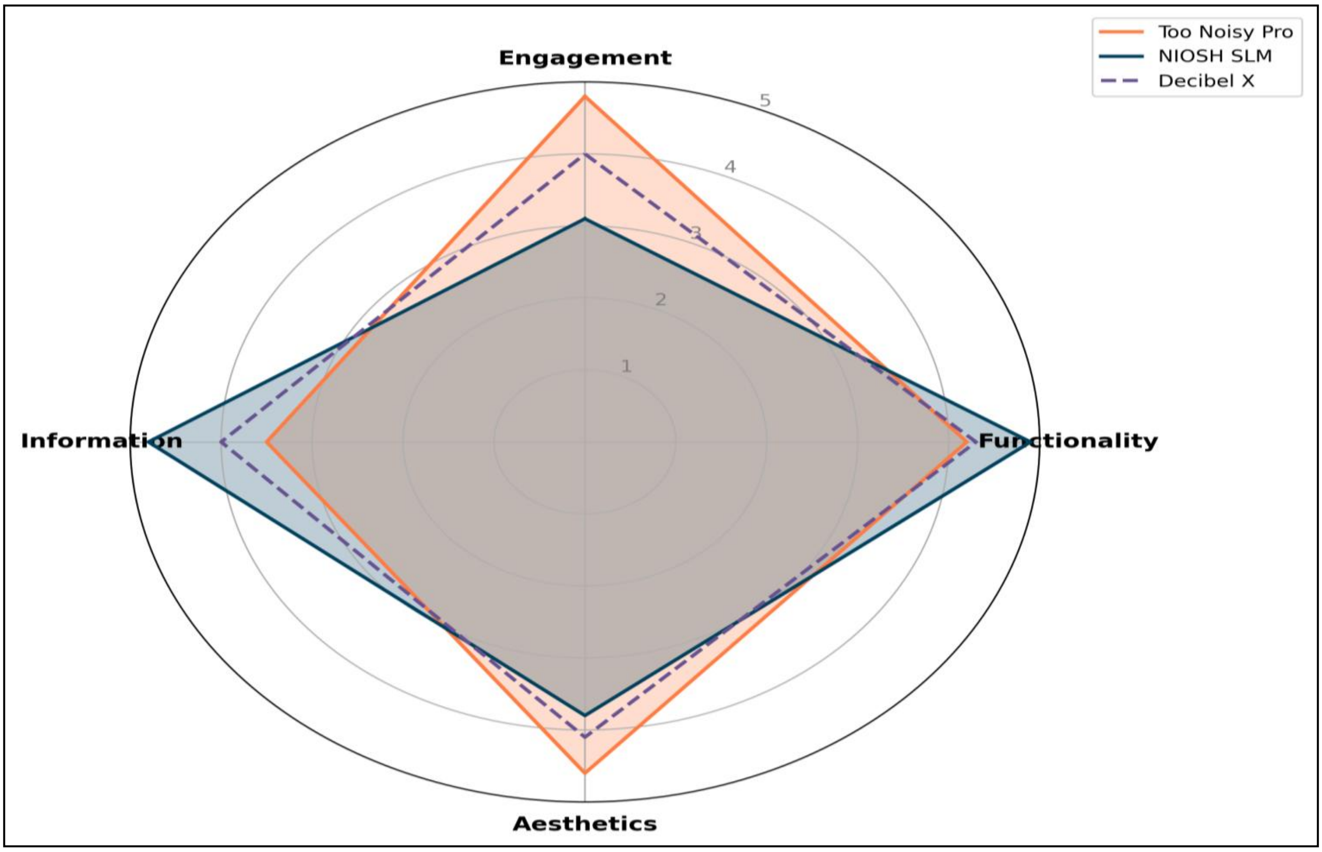

Figure 3: MARS usability scores by application.

DISCUSSION

This study elucidates the highly complex, multifactorial variables affecting the accuracy and utility of smartphone dosimetry across diverse acoustic, software, and socioeconomic environments. Previous crowdsensing initiatives and occupational health audits utilizing Android devices have consistently noted significant data variance and unreliability.[17-20] The findings of our targeted cross-platform analysis provide a definitive mechanical explanation for this phenomenon, confirming that the variance is not solely a hardware limitation, but rather a profound software calibration disconnects.

The Walled Garden ecosystem of iOS allows developers to create applications that interact predictably with known hardware. Consequently, apps like the NIOSH SLM and the iOS version of Decibel X can function remarkably close to class 2 SLM standards. The Android ecosystem, however, represents a highly fragmented landscape heavily reliant on aggressive native DSP and automatic gain control (AGC). These built-in algorithms are engineered primarily to enhance human voice clarity during phone calls by actively identifying and suppressing loud, high-frequency, or impulsive environmental noises-the exact hazardous stimuli that a clinician is attempting to measure. The fact that the cross-platform "Decibel X" application vastly overestimates noise (+4.60 dBA) while the native "sound meter" application vastly underestimates noise (-5.40 dBA) on the exact same Xiaomi budget hardware definitively proves that generic developer algorithms fail to account for the array of MEMS microphones and native DSP filters present in the Android market. The developers of Decibel X likely calibrated their Android algorithm against a different subset of hardware, resulting in a systemic mathematical overshoot when deployed on our specific test devices.

These findings directly align with and expand upon the observations made by Serpanos et al who evaluated smartphone SLM applications in clinical rooms.[12] While their study noted iOS superiority in controlled settings, our inclusion of impulsive urban noise demonstrates that Android error margins are not static; they scale disproportionately in complex environments. Furthermore, Robinson and Tingay highlighted the challenges of applying class 2 standards to uncalibrated smartphones in problematic workplace environments.[9] Our spectral error mapping confirms their hypothesis that high-frequency acoustic environments (above 4000 Hz) present the most significant vulnerability for consumer MEMS microphones, particularly those governed by aggressive noise-canceling firmware. Unlike steady-state noise profiles common in Western industrial models (e.g., generator hums), the Indian acoustic soundscape is highly impulsive. Studies like those by Shim et al which primarily evaluated occupational noise assessment in controlled settings, may ultimately underestimate the real-world failure rate of budget smartphones which actively suppress the sudden, sharp peaks characteristic of urban traffic and unorganized sector environments.[18]

For the otolaryngologist and audiologist, this poses a critical, potentially dangerous challenge for occupational noise assessment and tele-health monitoring. The "Bharat" demographic-representing the vast majority of the Indian population-relies almost exclusively on budget-tier Android devices. If a clinician recommends a generic decibel app to a patient utilizing a sub-₹15,000 smartphone, the resulting data is virtually meaningless out-of-the-box. As our impulsive noise testing demonstrated, these budget devices will actively suppress dangerous, hazardous noise peaks (like industrial machinery or urban traffic horns), providing the patient with dangerous false reassurances that their environment is safe. This carries severe medicolegal and occupational ramifications. If factory safety officers or workers in the unorganized sector utilize native Android applications that systematically underestimate hazardous noise by 5 dBA, they may inadvertently violate statutory safety compliance thresholds, leaving the workforce chronically unprotected against NIHL.[18]

Furthermore, evaluating these tools beyond technical acoustic physics to include clinical usability yielded crucial insights. The findings from the MARS assessment highlight the significant cognitive load placed on healthcare workers and patient families in high-stress environments. Interpreting raw, fluctuating numeric decibel data causes fatigue. The superior performance of visually engaging applications (e.g., "Too Noisy Pro") in the NICU demonstrates that intuitive visual cues-such as a dynamic interface changing from a smile to a frown-provide immediate, actionable feedback that more effectively drives protective behavioral changes in a fast-paced clinical setting.[14]

The ASHA/PHC tele-audiology calibration protocol

As participatory soundscape mapping and decentralized tele-audiology networks rapidly expand across developing nations, clinical paradigms must adapt to the technological realities of the population.[21,22] Relying on automated smartphone audiometry and environmental telemetry in rural networks is an essential mechanism for addressing the massive burden of NIHL, but it is currently fraught with unacceptable calibration errors. Therefore, we propose the implementation of a formalized "primary health centre (PHC) calibration protocol." This protocol is designed specifically for resource-limited settings where precision class 1 SLMs are entirely unavailable, but basic audiometric equipment is present.

The clinical setup

Accredited social health activists (ASHA) or rural medical officers can utilize standard, highly portable screening audiometers (commonly available in Indian PHCs).

The stimulus

The clinician sets the audiometer to output a 70 dB HL narrow band noise (NBN) signal centered at 1000 Hz, delivered via a free-field speaker or carefully positioned headphone transducer at a standardized distance of 1 meter.

The measurement

The patient launches the designated SLM app on their personal smartphone (regardless of whether it is a flagship or budget Android) and records the ambient reading of the 70 dB HL tone.

Deriving the correction factor

If the audiometer outputs a verified 70 dB HL, but the patient's budget Xiaomi phone registers only 64 dBA, the clinician establishes a biological "Correction Factor" of +6 dB for that specific patient's device.

Clinical application

The patient is formally instructed to add +6 dB to all future occupational or environmental readings taken in their daily life.

This straightforward biological check effectively bypasses the software-hardware calibration disconnect, allowing clinicians to transform highly inaccurate, budget-tier consumer electronics into viable, individualized screening tools for occupational health. Looking forward, as this calibration protocol scales across tele-audiology networks, public health administrators could aggregate these device-specific correction factors. Tracking this data would allow for the visualization of specific hardware failure trends over time, establishing a robust, data-driven framework to identify which budget smartphone models are fundamentally unsuitable for acoustic telemetry even after calibration.[21]

Limitations

While this study rigorously evaluated 10 application configurations and three specific device tiers, the consumer electronics market is characterized by continuous, rapid evolution. Software updates to applications or operating system firmware may retroactively alter algorithm compliance with international electroacoustic standards.[15] Furthermore, this study evaluated the built-in MEMS microphones. Future research should evaluate the efficacy of utilizing standardized external plug-in microphones (via USB-C or Lightning ports) as a method of bypassing the internal device processing entirely, potentially unifying the hardware variable across both iOS and Android platforms.

Smartphone sound level meter applications display significant platform-dependent variance, largely due to a software-hardware calibration disconnect in the Android ecosystem rather than singular hardware failure. Budget-tier Android devices utilize aggressive internal DSP that dangerously suppresses and underestimates loud, impulsive environmental noises (e.g., urban traffic horns) by upwards of 12 dBA. Data generated from uncalibrated patient smartphones cannot be treated uniformly by clinicians and is insufficient for standardized occupational screening. Implementing a biological calibration protocol at the PHC level using standard screening audiometers allows clinicians to derive patient-specific correction factors, making decentralized tele-audiology dosimetry viable in resource-limited settings. Applications utilizing intuitive visual feedback (e.g., changing colors or facial expressions) demonstrated vastly superior clinical utility in high-stress medical environments compared to raw numeric decibel displays.

CONCLUSION

Smartphone SLM applications offer immense, democratizing potential for tele-audiology and public health monitoring. However, profound cross-platform discrepancies and extreme hardware fragmentation-particularly within the budget-tier Android devices that dominate developing nations-severely limit their "out-of-the-box" reliability. Otolaryngologists cannot treat all smartphone data uniformly. Clinicians must interpret app-based noise telemetry with extreme caution, explicitly recognizing the failures of these devices against impulsive urban noise and high-frequency hazardous tones. Implementing individualized, biological calibration protocols at the primary care level is an absolute requisite before integrating patient-generated smartphone dosimetry into clinical decision-making and hearing conservation programs.

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REFERENCES

1. World Health Organization. Hearing loss due to recreational exposure to loud sounds: A review. Geneva: WHO; 2015. Available at: https://iris.who.int/handle/10665/154589. Accessed on 3 June 2026.
2. Neitzel RL, Swinburn TK, Hammer MS, Eisenberg D. Economic Impact of Hearing Loss and Reduction of Noise-Induced Hearing Loss in the United States. J Speech Lang Hear Res. 2017;60(1):182-9.
3. International Electrotechnical Commission. IEC 61672-1:2013 Electroacoustics-Sound level meters. Geneva: IEC; 2013.
4. Ventola CL. Mobile devices and apps for health care professionals: uses and benefits. P T. 2014;39(5):356-64.
5. Williams W. The accuracy of sound level meter 'apps'. Acoust Aust. 2013;41(1):108-10.
6. Nast DR, Speer WS, Le Prell CG. Sound level measurements using smartphone "apps": useful or inaccurate? Noise Health. 2014;16(72):251-6.
7. Fausti SA, Wilmington DJ, Helt PV, Helt WJ, Konrad-Martin D. Hearing health and care: the need for improved hearing loss prevention and hearing conservation practices. J Rehabil Res Dev. 2005;42(4-2):45-62.
8. Robinson DP, Tingay J. Comparative study of the performance of smartphone-based sound level meter apps, with and without the application of a " IEC-61094-4working standard microphone, to IEC-61672 standard metering equipment in the detection of various problematic workplace noise environments. Inter Noise. 2014;1-10.
9. Serpanos YC, Renne B, Schoepflin JR, Davis D. The Accuracy of Smartphone Sound Level Meter Applications with and Without Calibration. Am J Speech Lang Pathol. 2018;27(4):1319-28.
10. Kardous CA, Shaw PB. Evaluation of smartphone sound measurement applications. J Acoust Soc Am. 2014;135(4):EL186-92.
11. Roberts B, Kardous C, Neitzel R. Improving the accuracy of smart devices to measure noise exposure. J Occup Environ Hyg. 2016;13(11):840-6.
12. Serpanos YC, Schoepflin JR, Cox SR, Davis D. The Accuracy of Smartphone Sound Level Meter Applications (SLMAs) in Measuring Sound Levels in Clinical Rooms. J Am Acad Audiol. 2021;32(1):27-34.
13. American National Standards Institute. ANSI S3.1-1999 (R2018) Maximum Permissible Ambient Noise Levels for Audiometric Test Rooms. New York: ANSI. 2018.
14. Stoyanov SR, Hides L, Kavanagh DJ, Zelenko O, Tjondronegoro D, Mani M. Mobile app rating scale: a new tool for assessing the quality of health mobile apps. JMIR Mhealth Uhealth. 2015;3(1):e27.
15. Celestina M, Hrovat J, Kardous CA. Smartphone-based sound level measurement apps: Evaluation of compliance with international sound level meter standards. Appl Acoust. 2018;139:119-28.
16. Sun K, Kardous CA, Shaw PB, Kim B, Mechling J, Azman AS. The potential use of a NIOSH sound level meter smart device application in mining operations. Noise Control Eng J. 2019;67(1):23-30.
17. Bocher E, Judicaël P, Gwenaël G, Gwendall P, Nicolas F, Arnaud C, et al. Crowdsourcing of Noise Map Pollution using Smartphones. European NEtwork for Redistributing Geospatial Information; 2015.

18. Shim H, Lee S, Hwang S. Accuracy of smartphone noise measurement applications for occupational noise assessment. Saf Health Work. 2 020;11(1):119-23.
19. Kraft R, Reichert M, Pryss R. Towards the Interpretation of Sound Measurements from Smartphones Collected with Mobile Crowdsensing in the Healthcare Domain: An Experiment with Android Devices. Sensors (Basel). 2021;22(1):170.
20. Khan H, Findlay C, Stevenson RA, Singh T. Evaluating the Accuracy of Android Applications in Monitoring Environmental Noise Levels. Cureus. 2025;17(3):e81471.
21. van Tonder J, Swanepoel W, Mahomed-Asmail F, Myburgh H, Eikelboom RH. Automated Smartphone Threshold Audiometry: Validity and Time Efficiency. J Am Acad Audiol. 2017;28(3):200-8.
22. Brambilla G, Pedrielli F. Smartphone-Based Participatory Soundscape Mapping for a More Sustainable Acoustic Environment. Sustainability. 2020;12(19):7899.

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