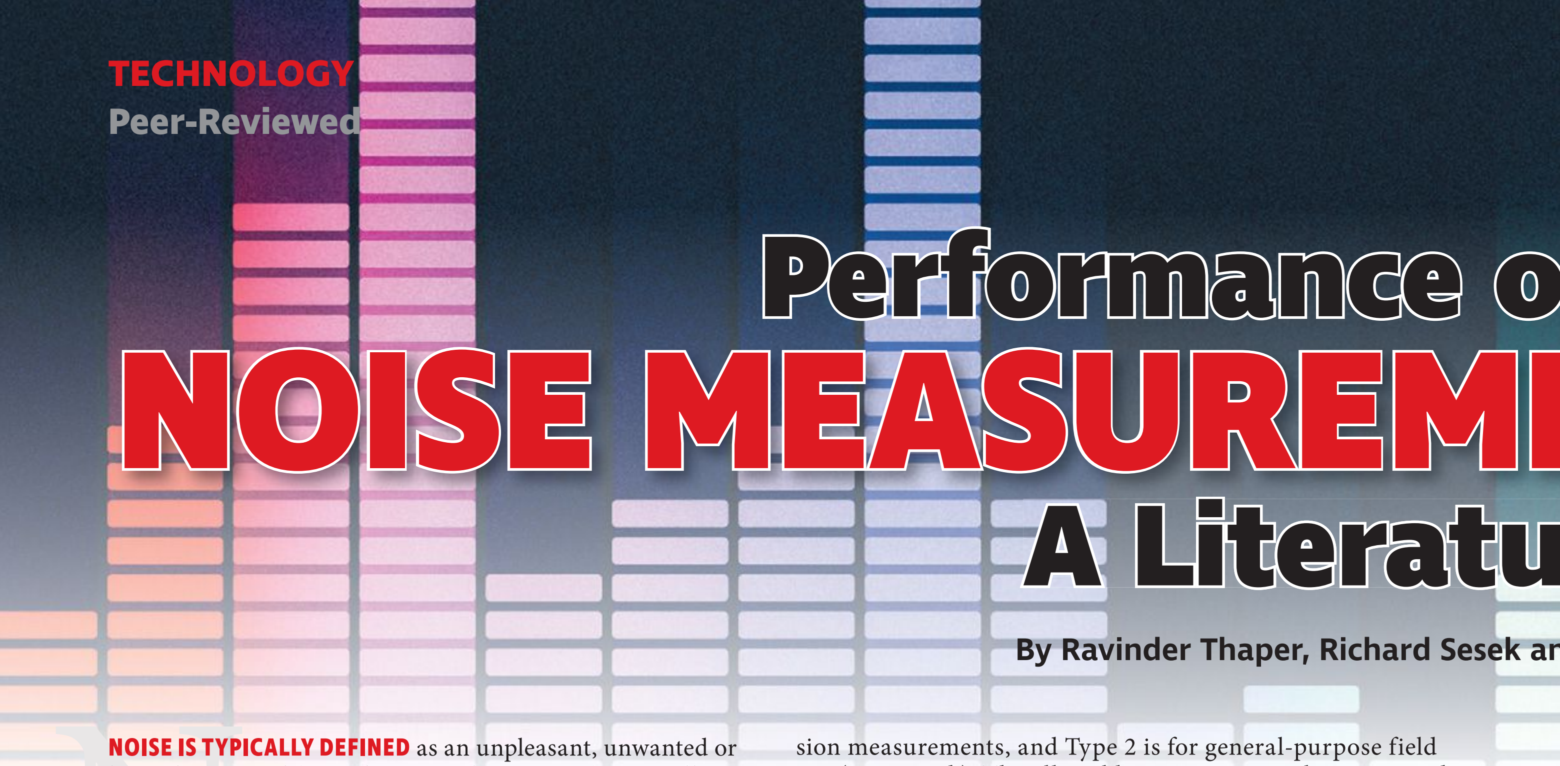

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NOISE MEASUREM
A Literatu

By Ravinder Thaper, Richard Sesek ar

NOISE IS TYPICALLY DEFINED as an unpleasant, unwanted or hazardous sound (Murphy & Harshman, 2012). Virtually everyone is exposed to noise, but many often underestimate the adverse health consequences of excessive long-term noise exposure such as increased situational danger and noise-induced hearing loss (NIHL). Hearing loss may contribute to incidents and injuries, as this perceptual loss may prevent a person from recognizing warning signals or imminent danger associated with the use of equipment or tools (Hager, 2002). According to NIOSH (2019), more than 17% of the working population has experienced hearing loss, with approximately one in four of these hearing losses being work-related. As noise exposure can pose such a significant health risk to the working population, it is critical to properly assess workers' exposure by accurately measuring noise exposure, then applying appropriate abatement measures with engineering controls of the noise source prioritized.

A sound level meter (SLM) and noise dosimeter are the most commonly used instruments to measure occupational noise levels (CCOHS, 2020). An SLM is usually positioned in the location of concern while a dosimeter is worn on the body with a microphone attached to the worker's collar or shoulder. Dosimeters are preferred in personal exposure assessments, while SLMs are typically used for screening purposes (i.e., area sampling), a source control purpose or as an alternative when dosimeters are not feasible (OSHA, n.d.-a). Some high-end SLM models also contain the functions of dosimeters. Sound measurement instruments can be classified into three grades according to ANSI S1.4-1983: Type 0, Type 1 and Type 2. Type 0 is a laboratory standard, Type 1 is for field and laboratory precision measurements, and Type 2 is for general-purpose field use (ANSI, n.d.). The allowable error in a reverberant sound field is approximately ±1.5 dB for a Type 1 instrument and ±2.3 dB for Type 2 (ANSI, n.d.). OSHA considers Type 1 and Type 2 instruments to have an accuracy of ±1 dB(A) and ±2 dB(A), respectively (Kardous & Shaw, 2014; OSHA, n.d.-a). Type 2 devices meet the OSHA minimum requirement and are widely used for workplace evaluations. The OSHA permissible exposure limit (PEL) for an 8-hr work shift [i.e., 8-hr time-weighted average (TWA)] is 90 dB(A), which is considered a dose of 100% (OSHA, n.d.-b). SLMs used in occupational exposure assessments are required to have basic features such as frequency weighting, response rate and threshold level. Additional features such as exchange rate, criterion level and criterion time are needed when converting a measurement result in TWA into a dose for comparison to dosimeter outputs.

SLMs and dosimeters can cost thousands of dollars and may not be practical for many small businesses or individuals to purchase and use. To overcome this challenge, workers and some safety professionals have begun using sound measurement applications (apps) on smart devices to measure noise sources or personal exposure levels in the workplace (Roberts et al., 2016). The smartphone noise measuring apps can be used as a quick check if sound levels are high (Thaper, Carter et al., 2019; Thaper, Gibson et al., 2019). The ability to measure workplace noise levels using a smart device app, especially on a smartphone, provides practical benefits such as low cost, easy accessibility, compact size, powerful computational ability, built-in high-resolution display and the potential to be used as a Type 2 SLM. However, because noise measurement apps and smart devices are continually changing and evolving, the accuracy of sound measurements may depend on the choice of the app, the make or model of the smart device, the use of an internal or external microphone, and the system software running on the smart device. A large variety of sound measurement apps have been available, and the accuracy of the apps has been evaluated to determine their capability to be used as an alternative sound monitoring tool. To the best of the authors' knowledge, there is no comprehensive review on the performance of existing sound measurement apps in the literature. In this study, the authors sought to summarize the peer-reviewed literature on the accuracy of sound

KEY TAKEAWAYS

- **Occupational hearing loss is a severe problem that affects millions of U.S. workers every year. However, the high cost of professional-grade sound measurement instruments limits access for workers and many businesses.**
- **Many sound measurement applications for smart devices have been developed as potential alternatives to costly sound measurement instruments.**
- **This article reviews the current literature on the sound measurement applications with two objectives: summarize the accuracy of various smartphone sound measurement applications and identify applications with features suitable for occupational exposure assessment.**

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d Jonghwa Oh

measurement apps primarily on smartphones to learn which apps can be used for accurate noise measurement and subsequently used for general noise control purposes. In addition, the features of the apps were reviewed when available to identify which apps can be potentially used in occupational exposure assessment.

Methodology

A keyword search for "smartphone sound measurement applications" was performed using Google Scholar to identify relevant peer-reviewed journal articles. Library subscriptions at the authors' universities allowed for a thorough internet search and access to all identified journals, which resulted in 195 total articles. The title of each paper was assessed for its relevance to the accuracy of smartphone apps that measure sound, which reduced the number of papers to 25. Finally, each paper's abstract was assessed for mention of smartphone noise apps that measure occupational or environmental noise, and this reduced the number of relevant papers to 15. These remaining papers were analyzed and summarized for this review.

Results

Accuracy of Sound Measurement Applications

The findings from this review illustrate that there are hundreds of sound measurement apps available on smart devices today, but with varying levels of measurement accuracy and precision sound. Table 1 (p. 40) shows the list of 24 sound measurement apps examined in the reviewed studies.

Table 2 (pp. 42-43) summarizes the sound measurement conditions and results of the 24 sound measurement apps. The results column (column 6) represents the mean difference, standard error and standard deviation from the reference sound levels (column 4) measured with the smart devices (column 2) with the apps installed (column 5) mentioned in the respective studies. Keene et al. (2013) examined six sound measurement apps: Decibel 10th, Decibel Meter and dB Volume on iPhones, and Sound Meter (V2.1 by Borce Trakkovski), Noise Meter and Sound Meter (V1.4.10 by Smart Tools Co.) on Android phones. Pink noise measurements from a Type 1 SLM at 85- and 95-dB hearing levels (HL) were compared with all readings from the apps and ±3 dB was set as a tolerance in the study. SLM measurements were in A-weighted values while app measurements were in default (i.e., indicating unweighted measurements). At 85 dB HL, all readings from two apps, Decibel 10th and Decibel Meter, were within a ±3 dB tolerance, while at 95 dB HL none of the apps were 100% within the tolerance. From one app, dB Volume, 22% of the readings were within ±3 dB at 95 dB HL and the dB Volume app had 67% of all of its readings within the tolerance at 85 dB HL.

Kardous and Shaw (2014) evaluated 10 sound measurement apps on iOS-platform-based smart devices using pink noise with a 20 to 20,000 Hz at 65 to 85 dB and compared results with reference values obtained using a Type 1 SLM. For A-weighted sound measurements, SoundMeter, NoiSee and Noise Hunter showed mean differences within ±2 dB(A) of the reference sound level measurements, and for unweighted sound measurements, NoiSee, SoundMeter and SPLnFFT had mean differences within 2 dB of the reference values. In a follow-up study by Kardous and Shaw (2016), the accuracies of the four best performing apps from the previous study (i.e., SoundMeter, NoiSee, Noise Hunter and SPLnFFT) were evaluated on iPhones with calibrated external microphones, i436 and iMM-6, under the same experimental conditions as the previous study. It was observed that the mean difference from the references (-0.023 ± 0.530 dB) was less than that of the internal microphones (1.646 ± 3.795 dB).

The accuracy of five sound measurement apps on an iPhone (i.e., dB Volume, Advanced Decibel, SPLnFFT Noise Meter, SPL and SoundMeter) was assessed by Nast et al. (2014). App sound measurements were conducted at 50 to 95 dB HL with varied frequencies from 0.25 to 8 kHz using A- and C-weighting filters, and results were compared with Type 1 SLM measurements. The SoundMeter app showed the smallest differences from the reference measurements at both frequency weightings, with mean differences within 1 to 2 dB(A) and typically 3 dB(C) across the sound level and frequency conditions. They also performed background noise measurements and it was found that all app measurements were at least 5 dB higher than the SLM measurements.

Ibekwe et al. (2016) examined one sound measurement app, Androidboy1, on three Android platform-based smartphones using environmental noise at different locations in Abuja, Nigeria. App measurement results were compared with sound measurements obtained with a Type 2 SLM. Consistent readings were shown between smartphones and 92.9% of total

TABLE 1

LIST OF SOUND MEASUREMENT APPLICATIONS

Application name	Developer	Version	Cost ($)	Operating system	Reference
Adv Decibel Meter	Amanda Gates	2.0	0.99	iOS	Kardous & Shaw, 2014; 2016
Advanced Decibel	Darren Gates	1.0	0.99	iOS	Nast et al., 2014
Androidboy1	Smart Tools Co.	UA	0.00	Android	Ibekwe et al., 2016
Decibel 10th	SkyPaw Co. Ltd	UA 4.3.5 8.0	0.00	iOS	Keene et al., 2013; McLennon et al., 2019; Sakagami et al., 2019
Decibel X	SkyPaw Co. Ltd	8.0	0.00	Android	Sakagami et al., 2019
Decibel Meter	Byoughun Jang	UA	0.00	iOS	Keene et al., 2013
Decibel Meter Pro	Performance Audio UA	2.0.5	1.00	iOS	Kardous & Shaw, 2014; 2016; Murphy & King, 2016
		4.7			Sakagami et al., 2019
Decibel Meter Pro	Vlad Polyanskiy Tools	UA	0.00	Android	Sakagami et al., 2019
Decibel Pro	BSB Mobile Solutions Tolls	1.4.22	4.99	Android	Murphy & King, 2016
DB Volume	DSP Mobile	1.0.5	0.00	iOS	Nast et al., 2014
DB Volume	DSP Mobile	UA	0.00	iOS	Keene et al., 2013
iSPL Pro	Colours Lab	1.1.4	5.99	iOS	Kardous & Shaw, 2014; 2016
NIOSH Sound Level Meter (SLM)	EA LAB	UA	0.00	iOS	Sun et al., 2019
		Mentioned as NoiSee 2.0	0.00		Celestina et al., 2018
		1.0.4	0.00		Jacobs et al., 2020
vNoise Exposure	Arbetsmiljoverket	2.0.1	0.00	iOS	McLennon et al., 2019
Noise Hunter	Inter.net2day	1.0.1	6.00	iOS	Kardous & Shaw, 2014; 2016
Noise Meter	JINASYS	2.1	0.00	Android	Murphy & King, 2016; Keene et al., 2013
NoiSee	IMS Merilni Sistemi	1.0	0.99	iOS	Kardous & Shaw, 2014; 2016
	EA Lab	UA	0.99		Roberts et al., 2016
(Real) SPL Meter	BahnTech	1.0	0.99	iOS	Kardous & Shaw, 2014; 2016
Sound Level Analyzer (SLA) Lite-Simple dB Meter	Toon, LLC	1.0.0	0.00	iOS	McLennon et al., 2019
Sound Level Analyzer (SLA) Lite	Toon, LLC	1.3 1.0.0	5.00	iOS	Murphy & King, 2016
Sound Level Meter	Mint Muse	1.5	19.99	iOS	Kardous & Shaw, 2014; 2016
Sound Level Meter Pro		2.2			Serpanos et al., 2018
Sound Level Meter (Voice Meter)	Seong Eon Kim	1.8	0.00	iOS	McLennon et al., 2019
Sound Log	Australian Hearing Services	UA	0.00	iOS	Sakagami et al., 2019
Sound Meter- Noise Power Level and Decibel Meter	LQH Apps	1.0.0	0.00	iOS	McLennon et al., 2019
Sound Meter	Smart Tools Co.	1.6 1.4.10	0.00	Android	Murphy & King, 2016 Keene et al., 2013
	Borce Trajkovski	2.1	0.00	Android	Keene et al., 2013
	Faber Acoustical	3.3.1	20.00	iOS	Kardous & Shaw, 2014; 2016
		3.1	10.00		Nast et al., 2014
		UA	20.00		Roberts et al., 2016
SPL	Studio Six Digital	2.6	0.00	iOS	Nast et al., 2014
SPL Pro	Andrew Smith	3.6	0.99	iOS	Kardous & Shaw, 2014; 2016
SPLnFFT	Fabien Lefebvre	4.0	3.99	iOS	Kardous & Shaw, 2014; 2016
		UA	3.99		Roberts et al., 2016
		1.1	3.61		Murphy & King, 2016
SPLnFFT (Noise Meter)		3.3	3.99	iOS	Nast et al., 2014
UE SPL	Logitech Inc.	2.1.1	0.00	iOS	Murphy & King, 2016
Analyzer	DSP Mobile	2.7.2	14.99	iOS	Serpanos et al., 2018
SPL Meter	Andrew Smith, Studio Six Digital	9.3	0.99	iOS	Serpanos et al., 2018
Cart_ASUR	Pierre Aumond	UA	UA	Android	Aumond et al., 2017
Noise Exposure	Arbetsmilj€overket	2.0.1	0.00	Android	McLennon et al., 2019
Decibel 10th	SkyPaw Co Ltd.	1.4.1	0.00		
Sound Meter- Decibel	Melon Soft	1.1.1	0.00		
Sound Meter	Abc Apps	3.1.6	0.00		
Sound Meter & Noise Detector	Tools Dev	1.2	0.00		

Note. UA: Unavailable from the reference.

readings were within ±2 dB(A) of the reference values measured with an SLM.

In the study by Murphy and King (2016), seven apps [i.e., Sound Level Analyzer (SLA) Lite, SPLnFFT, dBMeter Pro, UE SPL, Sound Meter, Noise Meter and Decibel Pro] were tested on 65 iOS and 35 Android smartphones. Broadband white noise at 50, 70 and 90 dB(A) along with background noise at 27 dB(A) was used, and overall, the apps were less accurate at measuring the low background and high [i.e., 90 dB(A)] noise levels. The SLA Lite app on iOS phones was the best with mean differences within ±1 dB(A) of the reference values at all sound levels examined. SPLnFFT on iOS phones were followed with mean differences within 3 dB(A) except at the background level.

Roberts et al. (2016) tested three sound measurement apps on iOS smart devices, including NoiSee, SPLnFFT and SoundMeter, previously examined by Kardous and Shaw, to evaluate the effect of internal versus external microphones on the accuracy of the same type of smart devices. Pink noise at 60 to 100 dB(A) was measured with three iPods and results were compared with reference values measured with a Type 1 SLM. With internal microphones, none of the sound measurement apps showed a mean difference within 2 dB(A) of the reference values, especially the NoiSee app exceeded the limit of quantification (LOQ) at 95 and 100 dB(A).

Aumond et al. (2017) developed an Android app Cart_ASUR and tested its accuracy in measuring urban noise pollution. They found that mobile phones can be used as reliable tool to measure noise after calibration. Serpanos et al. (2018) tested three apps (i.e., Analyzer, Sound Level Meter Pro and SPL Meter) with and without calibration at frequency of 1000-Hz narrowband noise and white noise at 20 to 100 dB, and in ambient noise in eight speech and hearing room environments. It was observed that calibration helped in measuring the sound precisely over 40- or 50-dB white noise and narrow band sound levels with accuracy of ±2 dB. It was reported that the inaccuracy for low-level noises may be attributed to sensitivity of inbuilt internal microphones of iOS devices, which are capable of measuring 30 to 130 dB, similar to the findings observed by Kardous and Shaw (2014) and Roberts et al. (2016). However, overestimation (at least 5 dB) was observed below 50 dB with or without calibration for ambient noise measurements in eight speech and hearing rooms.

In a study by Ventural et al. (2017), the researchers evaluated and calibrated Android phones for measurement with the Ambiciti app. They found that after removal of bias in the calibrated phones, the standard deviation was below 1.2 dB(A) for the range of sound levels between 45 and 75 dB. Also, windy conditions were found to cause an error of around 15 dB.

McLennon et al. (2019) evaluated apps and found that Android apps underreported sound levels. They concluded that sound measuring apps should not be used for compliance purposes. General correction factor is not applicable for accurate sound measurements regardless of type of phone, platform, type of sound and level of sound because reported sound levels were inconsistent. The range of error reported by iOS apps were smaller in comparison to Android apps. It was observed that the SLA Lite (iOS) app reported consistent measurements for occupational noises with low errors (-0.7 ± 2.1 dB) over all the sound levels tested. The Sound Meter and Noise Detector were found to be the top apps with a mean difference of 0.7 ± 6.4 dB for Android devices. However, due to large standard deviations, Sound Meter and Noise Detector Android apps were deemed inaccurate. The researchers Sakagami et al. (2019) conducted a study on the use of mobile devices with sound measuring apps to estimate the levels of urban acoustics in primary and secondary schools. They found that the iOS devices performed better with an error less than 1.5 dB compared to the Android devices.

NIOSH released an occupational sound measurement app, NIOSH SLM, available on iOS devices. Celestina et al. (2018) tested the NIOSH SLM app (which was initially called NoiSee app ver.2) according to relevant sound level meter standards, IEC 61672 and ANSI S1.4 (a nationally adopted IEC 61672 standard). Results showed that the app was well within the compliance requirements for Class 2 (e.g., Type 2) of the IEC/ANSI standard when used with an external microphone. In Sun et al. (2019), the NIOSH SLM app with the same external microphones previously used (i.e., i436 and iMM-6) was examined using industrial sound from a jumbo drill, a mining machine that usually creates noise above 100 dB(A), in laboratory and field environments. The average difference in equivalent continuous average sound level (L_{eq}) between the app measurements and a Type 1 SLM was 0.31 dB(A) in the laboratory test and 2.06 dB(A) in the field test. Most recently, Jacobs et al. (2020) evaluated the NIOSH SLM app with an uncalibrated iMM6 external microphone in different environments (i.e., coffee shop, restaurant, commuter train, spin class and office) across four U.S. cities. The mean differences in L_{eq} between the app measurement and reference dosimeter measurements were the smallest at the restaurant [-0.8 dB(A)], followed by spin class [2.1 dB(A)], train [2.2 dB(A)], office [2.3 dB(A)], and coffee shop [-11.3 dB(A)]. Overall, Noise Hunter, NoiSee, SoundMeter, Androidboy1, Sound Level Analyzer (SLA) Lite and NIOSH SLM apps showed mean differences within ±2 dB(A) of the respective reference sound measurements when using smart devices without external microphones. From the studies which used external microphones, the SoundMeter and NIOSH SLM apps showed mean differences within ±2 dB(A) of the respective reference values.

Functionality of Sound Measurement Applications for Occupational Noise Measurement

The features of the sound measurement apps are summarized in Table 3 (p. 44). While the majority of the listed applications were capable of reporting A-weighting sound levels, most of them were not able (or not reported) to provide the other major features necessary for occupational noise exposure assessment such as an exchange rate, threshold level and response rate. NoiSee, SoundMeter, SPLnFFT and the NIOSH SLM were the only four apps that allowed to choose such criteria.

Discussion

The use of different operating systems affected the accuracy and precision of sound measurement apps. In the Keene et al. (2013) study, which examined six different sound measurement apps on Android and iOS smartphones, the apps on Android devices in general underreported sound

TABLE 2

NOISE MEASUREMENT CONDITIONS & RESULTS BY APPLICATION

	Test conditions				
References	Smart devices	Microphone/microphone calibration	Reference sound/reference instrument	Application (platform)	Results
Keene et al., 2013	iPhone 4, iPhone 4s iPhone 5 Samsung Galaxy Ace Samsung Galaxy Samsung Galaxy Note 1 Samsung Galaxy Note 2 Nexus 4 LG Optimus One HTC Touch 1 HTC Desire	Internal built-in microphones/no calibration	Pink noise at 85 and 95 dB HL/Type 1 SLM (Larson-Davis 824)	Decibel 10 (iOS)	MD = 100 % measurements within ±3 dB at 85 dB HL MD = 0 % measurements within ±3 dB at 95 dB HL
				Decibel Meter (iOS)	MD = 100 % measurements within ±3 dB at 85 dB HL MD = 0 % measurements within ±3 dB at 95 dB HL
				dB Volume (iOS)	MD = 67 % measurements within ±3 dB at 85 dB HL MD = 22 % measurements within ±3 dB at 95 dB HL
				dB Volume (iOS) –Settings modified from default to dBA measurements	MD = 11 % measurements within ±3 dB at 85 dB HL MD = 11 % measurements within ±3 dB at 95 dB HL
				Noise Meter (Android)	MD = 0 % measurements within ±3 dB at 85 dB HL MD = 0 % measurements within ±3 dB at 95 dB HL
				Noise Meter (Android)- Settings modified from default to dBA measurements	MD = 0 % measurements within ±3 dB at 85 dB HL MD = 0 % measurements within ±3 dB at 95 dB HL
				Sound Meter ST (Android)	MD = 0 % measurements within ±3 dB at 85 dB HL MD = 0 % measurements within ±3 dB at 95 dB HL
				Sound Meter BT (Android)	MD = 33 % measurements within ±3 dB at 85 dB HL MD = 0 % measurements within ±3 dB at 95 dB HL
Kardous & Shaw, 2014	iPhone 3GS iPhone 4S iPhone 5 iPad 4th generation	Internal built-in microphones/no calibration	Pink noise with a 20 Hz to 20 kHz range at 65, 70, 75, 80, 85, 90, and 95 dB at a reverberant chamber/Type 1 random incidence microphone (Larson-Davis 2559)	Adv Decibel Meter (iOS)	MD = 3.78 dB, SE = 0.25 dB MD = -5.04 dB(A), SE = 0.27 dB(A)
				Decibel Meter Pro (iOS)	MD = -8.65 dB, SE = 0.32 dB MD = -13.17 dB(A), SE = 0.27 dB (A)
				iSPL Pro (iOS)	MD = -7.42 dB, SE = 0.27 dB MD = -2.57 dB(A), SE = 0.25dB (A)
				Noise Hunter (iOS)	MD = -12.21 dB, SE = 0.33 dB MD = -1.92 dB(A), SE = 0.27 dB(A)
				NoiSee (iOS)	MD = 1.97 dB, SE = 0.29 dB MD = -1.12 dB(A), SE = 0.25 dB(A)
				Sound Level Meter (iOS)	MD = 6.76 dB, SE = 0.29 dB MD = 3.60 dB(A), SE = .27 dB(A)
				SoundMeter (iOS)	MD = 1.75 dB, SE = 0.23 dB MD = -.51 dB(A), SE = .12 dB(A)
				(Real) SPL Meter (iOS)	MD = -5.58 dB, SE = .30 dB MD = -13.13 dB(A), SE = .27 dB(A)
				SPL Pro (iOS)	MD = 2.78 dB, SE = 0.23 dB MD = 2.48 dB(A), SE = .11 dB(A)
				SPLnFFT (iOS)	MD = 0.06 dB, SE = 0.35 dB MD = 2.27 dB(A), SE = .25 dB(A)
Nast et al., 2014	iPhone 4S	Internal inbuilt microphones/no calibration	50-, 70-, 85-, 90- and 95-dB hearing level (HL) at 0.25 to 8 kHz / Type 1 SLM (Brüel and Kjær 2250)	DB volume	MD = ±1-2 dB(A) at levels up to 80 dB at 1, 2, 4, and 8 kHz & 5-10 dB(A) at levels above 85 dB at 0.25, 0.5, 1, 2, 4, and 8 kHz MD = ±5 dB(C) for most frequency and HLs, MD = 7-8 dB(C) at and above 85 dB(C) at 2kHz
				Advanced Decibel	MD = -3-10 dB(A) across frequencies and HLs MD = ±5 dB(C) for most frequency and HLs, MD = 7-8 dB(C) at and above 85 dB(C) at 2kHz
				SPLnFFT (Noise Meter)	MD = -3-10 dB(A) across frequencies and HLs MD = 5-10 dB(C) across all frequencies and HLs
				SPL	MD = -3-10 dB(A) across frequencies and HLs MD = 8-10 dB(C) across all frequencies and HLs
				SoundMeter	MD = ±1-2 dB(A) for all frequencies and HLs MD = ±3 dB(C) for all frequencies and HLs
Ibekwe et al., 2016	Samsung Galaxy note 3 Nokia S Tecno Phantom Z	Internal inbuilt microphones/no calibration	Environmental noise within range of 47 to 91 dB(A) (for daytime) and 14 to 62 dB(A) (for nighttime)/Type 2 SLM (Extech 407730)	Androidboy1 (Android)	MD = ± 3 dB(A) during daytime in 2 locations MD = ± 4 dB(A) during night-time in 1 location MD (overall) = 92.9 % of total readings within ± 2 dB(A)
Kardous & Shaw, 2016	iPhone 5S iPhone 6	External microphones-i436 (MicW) & iMM-6 (Dayton Audio)/calibration performed	Pink noise with a 20 Hz to 20 kHz range at 65, 70, 75, 80, 85, 90, and 95 dB/Type 1 random incidence microphone (Larson-Davis 2559)	NoiSee (iOS)	MD = ±1 dB for both iMM-6 and i436 microphones
				SoundMeter (iOS)	MD = ±1 dB for both iMM-6 and i436 microphones
				SPL Pro (iOS)	MD = ±1 dB for both iMM-6 and i436 microphones
				SPLnFFT (iOS)	MD = ±1 dB for both iMM-6 and i436 microphones
Murphy & King, 2016	iPhone (4, 4s, 5, 5s, 5c, 6, +) Galaxy (Note 2, Note 3, s3, s3 slim, s3 mini, s4, s4 active, s5 Google (Nexus 5) HTC (One, One Mini 2, M8) LG (VS870, g2) Motorola (Droid 2, Droid MAXX, Moto X 2nd gen)	Internal inbuilt microphones/no calibration	Broadband white noise at 50, 70 and 90 dB(A) & background noise at 27 dB(A)/Type 1 SLM (Brüel and Kjær 2250)	Sound Level Analyzer (SLA) Lite (iOS)	MD = 0.57, -0.76, -0.55, and -0.55 dB(A) at 27, 50, 70, and 90 dB(A), respectively SD = 1.11, 1.21, 1.68. and 1.14 dB(A) at 27, 50, 70, and 90 dB(A), respectively
				SPLnFFT (iOS)	MD = 3.97, 2.90, 2.31, and 1.79 dB(A) at 27, 50, 70, and 90 dB(A), respectively SD = 1.20, 1.68, 2.55 and 3.02 dB(A) at 27, 50, 70, and 90 dB(A), respectively
				Decibel Meter Pro (iOS)	MD = 19.92, 4.23, -3.38 and -10.94 dB(A) at 27, 50, 70, and 90 dB(A), respectively SD = 2.95, 2.97, 2.80 and 3.10 dB(A) at 27, 50, 70, and 90 dB(A), respectively
				UE SPL (iOS)	MD = 9.70, 8.02, 7.68 and 1.89 dB(A) at 27, 50, 70, and 90 dB(A), respectively SD = 1.47, 1.56, 1.77 and 2.19 dB(A) at 27, 50, 70, and 90 dB(A), respectively
				Sound Meter (Android)	MD = 3.60, 3.11, 4.80 and -3.77 dB(A) at 27, 50, 70, and 90 dB(A), respectively SD = 6.0, 8.77, 9.34 and 9.40 dB(A) at 27, 50, 70, and 90 dB(A), respectively
				Noise Meter (Android)	MD = -6.73, -7.49, -5.09 and -13.65 dB(A) at 27, 50, 70, and 90 dB(A), respectively SD = 9.77, 8.87, 7.82 and 5.64 dB(A) at 27, 50, 70, and 90 dB(A), respectively
				Decibel Pro (Android)	MD = -5.21, -0.75, 2.86 and -5.11 dB(A) at 27, 50, 70, and 90 dB(A), respectively SD = 8.99, 8.58, 7.10 and 4.22 dB(A) at 27, 50, 70, and 90 dB(A), respectively

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Note. MD: Mean of differences between the app measurements and the reference sound levels. SE: Standard error. SD: Standard deviation. LOQ: Limit of qualification.

	Test conditions				
References	**Smart devices**	**Microphone/microphone calibration**	**Reference sound/reference instrument**	**Application (platform)**	**Results**
Roberts et al., 2016	iPhone 4 iPhone 4S iPhone 5S iPod 5G	Inbuilt internal microphones and external microphones-iMM 6 and i436/calibration for external microphones	Pink noise at 60 to 100 dB(A) with 5 dB(A) increments/Type 1 random incidence microphone (Larson Davis 2559)	NoiSee (iOS)	For iPods: MD = LOQ to 7.2dB(A) for internal microphone MD = -4.3 to 0 dB(A) for iMM-6 external microphone MD = 0 to 1.5 dB(A) for i436 external microphone
				SPLnFFT Noise Meter (iOS)	For iPods: MD = 1.5 to 2.8dB(A) for internal microphone MD = 1 to 2.1 dB(A) for iMM-6 external microphone MD = 1.2 to 2.3 dB(A) for i436 external microphone
				SoundMeter (iOS)	For iPods: MD = 2.2 to 3.4 dB(A) for internal microphone MD = -.1 to 0 dB(A) for iMM-6 external microphone MD = .4 to 1 dB(A) for i436 external microphone For smartphones: MD = -1.09 to 24.99 dB(A) for internal microphone MD = -.55 to .02 dB(A) for iMM-6 external microphone MD = -.01 to .82 dB(A) for i436 external microphone
	iPhone-6	External microphone MicW type i436/with calibration	38 to 117.4 dB	NoiSee (iOS)	MD = 0 – 1.44 dB(A) MD = 0 – 1.44 dB(C) MD = 0 – 1.40 dB(Z)
Aumond et al., 2017	HTC One X	Inbuilt internal microphone with calibration	Outdoor Noise Pollution/Type 1 SLM	Cart_AUSR	MD = 1.5 to 3 dB
Serpanos et al., 2018	iPhone 6S	Inbuilt internal microphone with and without calibration	a) 20 to 100 dB at 1000 Hz narrowband & white noise with 10 dB increments b) ambient noise measurements of eight speech and hearing rooms/Type 1 SLM (2250, Bruel & Kjaer)	Analyzer	MD = -.8 to 14.8 dB (with calibration at 20-100dB) MD = -6.9 to 6.9 dB (without calibration at 20-100dB) MD = -.2 to 9.7 dB (with calibration in hearing and speech room) MD = 5.0 to 16.7 dB (without calibration in hearing and speech room)
				Sound Level Meter Pro	MD = -.4 to 9.3 dB (with calibration at 20-100dB) MD = 2.5 to 9.6 dB (without calibration at 20-100dB) MD = 1.5 to 8.4 dB (with calibration in hearing and speech room) MD = 1.6 to 7.3 dB (without calibration in hearing and speech room)
				SPL Meter	MD = -.3 to 9.6 dB (with calibration at 20-100 dB) MD = .5 to 9.5 dB (without calibration at 20-100 dB) MD = 2.6 to 7.4 dB (with calibration in hearing and speech room) MD = 4.6 to 19.0 dB (without calibration in hearing and speech room)
Ventura et al., 2017	Asus (Nexus 7) HTC (One mini 2, Sensation 4 G) HUAWEI (U8860, Honor 5C, P6, Nexus 6P, P8 Lite, Y300) LGE (Nexus 5, 4, G3, Nexus 5X) Motorola (Moto G, Moto X) OnePlus (One, One Plus One, One Plus X) OPPO (X9076) Samsung Galaxy (Nexus, Ace2 X, Note, A3, A5, Ace Style, Alpha, Grand Prime, J5, Note 4, S3, S4, S4 Mini, S5, S5 LTE-A, S7 Edge) Sony (Xperia P, Z3 Compact, M4 Aqua Dual) WIKO (Rainbow UP 4G)	Inbuilt internal microphone with and without calibration	a) Pink Noise 40 to 95 dB with 20 Hz to 20kHz frequency b) Narrowband noises 57-78 dB/Cirrus Optimus red class 1 SLM	Ambiciti	MD = -32.5 to 6.9 dB (without calibration) SD = <1.2 dB (with calibration)
Celestina et al., 2018	iPhone 6	External microphone i436 (MicW)/calibration performed	94 dB at 1 kHz/SLM calibrator (Brüel & Kjær 4226)	NIOSH Sound Level Meter (SLM)	Deviation: 0.59, 0, 0.54, 0, and 1.44 dB(A) at 0.125, 1, 4, and 8 kHz, respectively Deviation: 0.37, 0, 0.53, and 1.44 dB(C) at 0.125, 1, 4, and 8 kHz, respectively Deviation: 0.4, 0, 0.5, and 1.4 dB at 0.125, 1, 4, and 8 kHz, respectively
Sun et al., 2019	a) Lab testing- iPhone 6 and 6S b) Field testing- iPhone 5S, 6, and 6S and iPod 4th Generation	External microphones: i436 (MicW) and iMM-6 (Dayton Audio)/calibration	Sound levels from the full course of drilling/Type 1 SLM (Larson-Davis Lx)		i436 microphone: MD = 1.1 dB(A) & SD = 1.6 dB(A) for laboratory test MD = -0.8 dB(A) & SD = 1.4 dB(A) for field test iMM6 microphone: MD = -0.5 dB(A) & SD = 0.9 dB(A) for laboratory test MD = -2.6 dB(A) & SD = 2.6 dB(A) for field test Overall: MD = 0.3 dB(A) & SD = 1.3 dB(A) for laboratory test MD = -2.1 dB(A) & SD = 2.4 dB(A) for field test
Jacobs et al., 2020	iPhone 6 iPhone 6S iPhone 6+ iPhone 7 iPhone 7+	Internal Microphone/no calibration External microphone: Dayton Audio iMM-6 / no calibration	Environmental noise from 47.7 to 101.7 dB(A) / noise dosimeter (3M Edge eg5)		(MD = Mean Dosimeter Reading – Smart Phone Reading) MD = 2.3 dB(A) for office environment MD = -11.3 dB(A) for coffee shop environment MD = 2.2 dB(A) for train environment MD = -0.8 dB(A) for restaurant environment MD = 2.1 dB(A) for spin class environment
McLennon et al., 2019	iPhone (6, 6 plus, 5s, SE, 4s), Samsung Galaxy S4, LG Nexus 5X, Huwawi Nexus 6p, LG Nexus 6p, Motorola G 2^{nd} Gen & Samsung Galaxy S7	Internal inbuilt microphones/no calibration	60, 70, 80 and 90 dB(A)/Larson Davis LxT	Noise Exposure Decibel 10^{th} Sound Meter-Noise Power Level and Decibel Meter Sound Level Analyzer (SLA) Lite- Simple dB Meter Sound Level Meter (Voice Meter) Noise Exposure (Android) Decibel 10th (Android) Sound Meter- Decibel (Android) Sound Meter Sound Meter & Noise Detector (Android)	MD = -18.8 dB to 18.6 dB (iOS devices) MD = -20.6 dB to 10.5 dB (Android devices)
Sakagami et al., 2019	iPhone XS iPad Air Android Tablet (Teclast P80X)	Internal inbuilt microphones with calibration	Pink Noise within range of 30-80 dB(A)	dB Meter Pro (iOS) Decibel Sound Meter Pro (Android) Decibel X (iOS & Android) SoundLog (iOS)	MD = 1.3 dB (dB Meter Pro and iPhone XS) MD = 0.6 dB (Decibel X and iPhone XS) MD = 1.6 dB (Sound Log and iPhone XS) MD = 1.5 dB (dB Meter Pro and iPad Air) MD = 1.8 dB (Decibel X and iPad Air) MD = 1.2 dB (Sound Log and iPad Air) MD = 1.8 dB (dB Meter Pro and Android Teclast P 80X) MD = 2.8 dB (dB Meter Pro and Android Teclast P 80X)

TABLE 3

FEATURES OF SOUND MEASUREMENT APPLICATIONS

Application	Latest version studied	Frequency weighting	Response rate	L_{eq} or TWA	Threshold level (dB)	Exchange rate (dB)	Dose	Data Export	Reference
				iOS Applications					
Adv Decibel Meter	2.0	A/C/Z	Slow/Fast	UA	UA	UA	UA	UA	Kardous & Shaw, 2014
Advanced Decibel	1.0	A/C	UA	UA	UA	UA	UA	UA	Nast et al., 2014
Analyzer	2.7.2	A	Slow/Fast	UA	UA	UA	UA	UA	Serpanos et al., 2018
dB Volume	UA	UA	UA	UA	UA	UA	UA	UA	Keene et al., 2013
DB volume	1.0.5	A/C	UA	UA	UA	UA	UA	UA	Nast et al., 2014
Decibel Meter®	UA	UA	UA	UA	UA	UA	UA	UA	Keene et al., 2013
Decibel Meter Pro	2.0.5	A/C/Z	Slow/Fast	UA	UA	UA	UA	UA	Kardous & Shaw, 2014
	4.7	A/B/C/Z	UA	UA	UA	UA	UA	UA	Sakagami et al., 2019
Decibel 10th	UA	UA	UA	UA	UA	UA	UA	UA	Keene et al., 2013
	4.3.5								McLennon et al., 2019
	8.0	A/B/C/Z	UA	UA	UA	UA	UA	UA	Sakagami et al., 2019
iSPL Pro	1.1.4	A/C/Z	Slow/Fast	UA	UA	UA	UA	UA	Kardous & Shaw, 2014
NIOSH Sound Level Meter (SLM)	UA	UA	UA	L_{eq} & TWA	80/90	3 dB/5 dB	Yes	Yes	Sun et al., 2019
	1.0.4	UA	UA	L_{eq} & TWA	80/90	3 dB/5 dB	Yes	Yes	Jacobs et al., 2020
	2.0	UA	UA	UA	UA	UA	UA	UA	Celestina et al., 2018
Noise Exposure	2.0.1	UA	UA	UA	UA	UA	UA	UA	McLennon et al., 2019
Noise Hunter	1.0.1	A/C/Z	Slow/Fast	TWA	UA	UA	UA	UA	Kardous & Shaw, 2014
NoiSee	1.0	A/C/Z	Slow/Fast	TWA	UA	3 dB/5 dB	UA	UA	Kardous & Shaw, 2014; 2016
	UA	A/C/Z	UA	TWA	UA	3 dB/4 dB/ 5 dB	Yes	No	Roberts et al., 2016
(Real) SPL Meter	1.0	A/C/Z	Slow/Fast	NA	UA	UA	UA	UA	Kardous & Shaw, 2014
Sound Level Analyzer Lite	1.3	A	UA	UA	UA	UA	UA	UA	Murphy & King, 2016
Sound Level Analyzer (SLA) Lite-Simple dB Meter	2.2	A	UA	UA	UA	UA	UA	UA	McLennon et al., 2019
Sound Level Meter	1.5	A/C/Z	Slow/Fast	UA	UA	UA	UA	UA	Kardous & Shaw, 2014
	1.8	UA	UA	UA	UA	UA	UA	UA	McLennon et al., 2019
Sound Log	UA	A/B/C/Z	UA	UA	UA	UA	UA	UA	Sakagami et al., 2019
Sound Level Meter Pro	2.2	A	Slow/Fast	UA	UA	UA	UA	UA	Serpanos et al., 2018
SPL Meter	9.3	A	Slow/Fast	UA	UA	UA	UA	UA	
SoundMeter	3.3.1	A/C/Z	Slow/Fast	L_{eq}	UA	3 dB/5 dB	UA	UA	Kardous & Shaw, 2014; 2016
	NA	A/C/Z	UA	Custom: Required in-app purchase for additional $20	UA	3 dB/4 dB/ 5 dB	Yes	Yes	Roberts et al., 2016
	3.1	A/C	UA	UA	UA	UA	UA	UA	Nast et al., 2014
Sound Meter- Noise Power Level and Decibel Meter	1.0.0	UA	UA	UA	UA	UA	UA	UA	McLennon et al., 2019
SPL Pro	3.6	A/C/Z	Slow/Fast	L_{eq}	UA	UA	UA	UA	Kardous & Shaw, 2014; 2016
SPLnFFT (as referred by Kardous and Shaw; Murphy & King) SPLnFFT NoiseMeter (as referred by Nast et al.)	4.0	A/C/Z	Slow/Fast	L_{eq}	UA	3 dB/5 dB	UA	Yes	Kardous & Shaw, 2014; 2016
	NA	A/B/C/Z	UA	Custom: Required additional in-app purchase	UA	3 dB/4 dB/ 5 dB	Yes	Yes	Roberts et al., 2016
	3.3	A/C	UA	UA	UA	UA	UA	UA	Nast et al., 2014
	1.1	A	UA	UA	UA	UA	UA	UA	Murphy & King, 2016
UE SPL	2.1.1	A	UA	UA	UA	UA	UA	UA	Murphy & King, 2016
				Android Apps					
Androidboy1	UA	A	UA	UA	UA	UA	UA	Yes	Ibekwe et al., 2016
Decibel X	8.0	A/B/C/Z	UA	UA	UA	UA	UA	UA	Sakagami et al., 2019
dB Sound Meter Pro	UA	A/C/Z	UA	UA	UA	UA	UA		
Decibel Pro	1.4.22	A	UA	UA	UA	UA	UA	UA	Murphy & King, 2016
	2.1	A	UA	UA	UA	UA	UA	NA	Murphy & King, 2016
Noise Meter	2.1	NA	UA	UA	UA	UA	UA	UA	Keene et al., 2013
Sound Meter	1.6	A	UA	UA	UA	UA	UA	UA	Murphy & King, 2016
	2.1	NA	UA	UA	UA	UA	UA	UA	Keene et al., 2013
Cart_ASUR	UA	A	UA	L_{eq}	UA	UA	UA	UA	Aumond et al., 2017
Ambiciti	UA	UA	UA	L_{eq}	UA	UA	UA	UA	Ventura et al., 2017
Noise Exposure	2.0.1	UA	UA	UA	UA	UA	UA	UA	McLennon et al., 2019
Decibel 10th	1.4.1	UA	UA	UA	UA	UA	UA	UA	
Sound Meter- Decibel	1.1.1	UA	UA	UA	UA	UA	UA	UA	
Sound Meter	3.1.6	UA	UA	UA	UA	UA	UA	UA	
Sound Meter & Noise Detector	1.2	UA	UA	UA	UA	UA	UA	UA	

Note. UA: Unavailable from the reference. *Z weighting = flat = unweighted

levels and the results were variable within an app as well as between the apps. The higher variability between Android apps could be partially explained by the larger number of phone models or manufacturers (i.e., eight Android models vs. three iPhone models). In a comparison of a platform in Murphy and King (2016), Android devices had smaller mean differences of the reference values (i.e., higher accuracy) than iOS devices, but in terms of precision, iOS devices performed better. The higher variability of Android devices could be related to smaller sample size as well as varied phone models. The authors also analyzed the difference in accuracy by smartphone age and concluded that newer phones in general were more accurate but less precise than older phones, leaving a question on whether the reason is related software or hardware (i.e., microphones). McLennon et al. (2019) concluded that at 90 dBA sound levels, Android devices underreported the measurements, which is a concern at higher sound levels.

Studies showed that the choice of frequency weighting filters (e.g., unweighing, A-weighting, C-weighting) affected the accuracy of the sound measurement apps, while certain apps did not have a filter option. Among the six apps Keene et al. (2013) tested, only two apps, dB Volume and Noise Meter, were able to change the measurements to A-weighted values; however, the results were less accurate when the change was made from default (i.e., unweighting) to A-weighting. In Nast et al. (2014), C-weighted measurements were in better agreement with the reference values than A-weighted measurements, which was possibly due to the more limited filtering of the C-weighting network. They frequently observed a large deviation of 5 to 10 dB differences in C-weighted measurements from the SPLnFFT app. However, the same app in a different version tested by Kardous and Shaw (2014) had best agreement with the reference values in unweighted sound levels. The two studies also tested another same app in a different version, SoundMeter, and similar results in A-weighted sound measurements were obtained.

Kardous and Shaw (2016) observed that the use of external microphones, i436 and iMM-6, improved the accuracy and precision of the measurements, the mean difference from the references (-0.023 ± 0.530 dB) was less than that of the internal microphones (1.646 ± 3.795 dB). Roberts et al. (2016) tested the same three sound measurement apps that Kardous and Shaw used and also showed high accuracy with external microphones. SoundMeter app measured with the i43 6and iMM-6 external microphones performed best with mean differences within ±1 dB(A) of the reference sound measurements, followed by SPLnFFT app with mean differences within 2.3 dB(A). The slightly lower accuracy compared to the Kardous and Shaw results could be because an A-weighting filter was employed in Roberts et al. In addition, the authors observed that the mean difference between the iOS smart devices (i.e., iPhones and iPods) using the same app (i.e., SoundMeter) and microphone was significant, indicating using an external microphone would not improve the accuracy across different generations of a device. Kardous and Shaw did not observe substantial difference between the two external microphones. However, Sun et al. (2019) employed the same type of external microphones and found that the i436 microphone, which complies with the Class 2 requirements of the IEC 61672 standard, was consistently more accurate than the iMM6 microphone both in the laboratory and field conditions when tested on the NIOSH SLM app.

The accuracy of sound measurement apps also seemed to be affected by test conditions (i.e., laboratory and field). Studies have been performed with the NIOSH SLM app to understand the performance of the app in different environments. In Sun et al. (2019), the NIOSH SLM app showed lower accuracy in field testing, which was possibly attributed to the effect of high ventilation volume (air currents) of the measurement location on the microphones. Jacobs et al. (2020) observed that the NIOSH SLM app measurements with an uncalibrated iMM6 external microphone deviated more from the reference values in lower noise environments (i.e., office) and environments with highly variable noise (i.e., spin class). The researchers are of the view that calibration of noise-measuring apps results in estimating sound levels precisely (McLennon et al., 2019; Serpanos et al., 2018).

Note that the results from some studies may not be objective, and comparison between studies may not be preferred because of the variability of measurement conditions between studies such as a reference sound source (i.e., pink/white noise, tool noise and environmental noise), reference sound level [background to over 100 dB(A)], measurement location (controlled lab setting and uncontrolled field setting), frequency weighting (i.e., A, C and Z) and reference instrument (Type 1 and Type 2).

Recommendations

The user should choose a noise measurement app based on the purpose of the noise evaluation, as each app provides different accuracy, precision and functions. For occupational noise exposure assessment, an app that provides an accuracy of a Type 2 SLM [i.e., ±2 dB(A)] is needed to meet the OSHA minimum requirement. Given the real-world scenario that nearly all the apps are not equipped with external microphones, one may consider calibrated external microphones to obtain more accurate and precise results. An A-weighting filter at a 20 Hz to 20 kHz frequency range must be available for human exposure assessment and a C-weighting filter may be recommend for peak sound measurements.

Conclusions

In this review, the authors summarized the current literature on the accuracy of sound measurement applications to determine whether the apps might be suitable as an alternative noise monitoring tool for a Type 2 SLM. Overall, six apps including Noise Hunter, NoiSee, SoundMeter, Androidboy1, Sound Level Analyzer (SLA) Lite and the NIOSH SLM showed the acceptable difference of ±2 dB(A) from the reference sound measurements under the respective sound measurement conditions. For occupational noise assessment, only four apps, NoiSee, SoundMeter, SPLnFFT and NIOSH SLM, were reported to have the essential functions such as an exchange rate, threshold level and response rate in addition to frequency weighting for occupational noise assessment. All of the apps except the SPLnFFT app performed well within ±2 dB(A) of accuracy as discussed. Although sound measurement apps and smart devices cannot be used for compliance purposes, those apps with acceptable accuracy can be utilized among workers or small businesses as a monitoring tool and to demonstrate the effectiveness of noise abatement actions.

There were several notable findings:

1. Android devices demonstrated a higher variability than iOS devices. The primary reason attributed to it could be lack of conformity or similarity regarding hardware from different manufacturers.

2. The accuracy of sound measurement apps decreased at lower and higher stimulus levels, possibly due to internal noise of microphones and microphone saturation.

3. The use of calibrated external microphones appeared to improve the accuracy and precision of the sound measurement apps.

4. The field studies that were far less available tended to result in less accurate measurements than laboratory studies.

The study has practical implications, as noise is unwanted sound and if an individual is exposed to high levels of noise every day in the workplace, this can potentially increase the chances of irreversible hearing loss. As the sound applications can measure the sound to a certain degree of accuracy and precision along with the advantage that they can be installed on smart devices, which are handy and cheaper as compared to professional SLMs, one can be informed about the levels of noise to which a person is exposed. Therefore, preventive measures such as hearing protection devices, engineering or administrative controls can be taken to reduce the noise exposure and thus avert the hearing loss. **PSJ**

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