Chronobiology International
The Journal of Biological and Medical Rhythm Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/icbi20

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To cite this article: Nahum M. Gabinet, Hassan Shama & Boris A. Portnov (2022) Using mobile phones as light at night and noise measurement instruments: a validation test in real world conditions, Chronobiology International, 39:1, 26-44, DOI: 10.1080/07420528.2021.1964520

To link to this article: https://doi.org/10.1080/07420528.2021.1964520

Published online: 31 Aug 2021.

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CHRONOBIOLOGY INTERNATIONAL
2022, VOL. 39, NO. 1, 26–44
https://doi.org/10.1080/07420528.2021.1964520

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ORIGINAL ARTICLE

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Using mobile phones as light at night and noise measurement instruments: a validation test in real world conditions

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ABSTRACT
Exposure to noise from road traffic and industries is known to be linked to various health dysfunctions, including hypertension, cardiovascular diseases and hearing loss. Exposure to artificial light at night (ALAN) is also increasingly recognized as being associated with ecosystem damage and various illnesses, including cancers, excessive weight gain and sleep disorders. However, measuring and monitoring these environmental risk factors by professional equipment are laborious and expensive, which impede large-scale research and various citizen science initiatives. In this study, we test a possibility that reliable noise and ALAN exposure estimates can be gathered using smartphones (SPs) sensors. To verify this assumption, we develop a standardized testing protocol, and use Andro-Sensor app, installed on three different Samsung Galaxy SPs – S7, S20FE5G, and SM520F, – to perform measurements of ALAN and noise in real-world conditions while comparing these measurements with measurements performed by professional (type 2) equipment – SL814 for noise and LX-1330B for illumination. The analysis of 3450 measurements, performed in two different locations in Israel, reveals that the SPs measurements and measurements performed by control instruments correlate strongly for noise (r = 0.76–0.94) and are nearly identical for ALAN (r = 0.998–0.999). The association between the two types of measurements is also found to be close to linear, with the slope of the trend line being close to 45° for ALAN and varying between 30° and 45° for noise, depending on the SPs used. Our conclusion is that the level of accuracy of ALAN measurements by SPs is greater for ALAN than for noise, which can make SPs a useful tool for large-scale ALAN studies that do not require the accuracy of professional instruments.

ARTICLE HISTORY
Received 25 May 2021
Revised 30 July 2021
Accepted 31 July 2021

KEYWORDS
Smartphones (SPs); artificial light at night (ALAN); noise; urban areas; exposure assessment

Introduction

The disruption of biological rhythms in humans is known to be linked to light pollution, resulting from exposure to various light-emitting devices, such as household appliances, tablets and cellular phones (see *inter alia*, Falchi et al. 2011; Green et al. 2017; Ohshima 2015; Smolensky et al. 2015; Zubidat and Haim 2017). As modern technology evolves, new sources of artificial light, such as light-emitting diodes (LEDs), constantly emerge (Montoya et al. 2017), which exacerbate the problem (Falchi et al. 2019).

Exposure to noise from traffic, industries and various household devices is another source of environmental pollution, known to be linked to various health dysfunctions, including hypertension (Babisch et al. 2001; Ising and Braun 2000; Maschke et al. 2002; Waye et al. 2003); cardiovascular diseases (Carter et al. 1994; Van Kempen et al. 2006); sleep disturbance and phase shift (Basner et al. 2011; Berg 2001; Buxton et al. 2011; Eberhardt et al. 1987; Freedman et al. 2001; Griefahn et al. 2008; Jakovljević et al. 2006; Okada and Inaba 1990; Passchier-Vermeer 2003; Smith et al. 2013; Stanchina et al. 2005; Topf 1992; Vallet et al. 1983); bad mood, depression, reduced cognitive performance (Carter 1996; Öhrström 1991; Waye et al. 2003; Wilkinson 1963) and hearing loss (Lewis et al. 2013; Lim et al. 2017).

However, most previous studies that investigated the effect of ALAN and noise on chronobiological disruption and related health effects in humans were ecological studies (*cf., inter alia* Gabinet and Portnov 2021; Zhang et al. 2018). Well-known limitations of such studies include exposure mis-specification due to differences between average and individual-level exposures and potential presence of uncontrolled confounders (Wakefield 2008). Concurrently, individual level studies, investigating ALAN and noise exposures, on the one hand, and their health effects, on the other, were mostly carried out in small population cohorts, and mainly under controlled laboratory conditions, and thus lack generality (e.g., Girschik et al. 2012).

Shortage of large-scale individual-level studies of ALAN and noise effects on humans in *real-world conditions* is largely due to the fact that monitoring these

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environmental pollutants by professional instruments is laborious and expensive, which impedes large-scale research and citizen-science initiatives (Zamora et al. 2017). In this respect, the widespread use of smart technologies, including smartphones (SPs), smart-bands, and data clouds (Kim et al. 2017; Petrolo et al. 2014; Su et al. 2011) can offer a valuable alternative for large-scale environmental data gathering for individual-level research.

According to the Pew Research Center, the level of smart technology proliferation in the world constantly increases, with about 70 million people in the USA alone (21%) owning smartwatches and smart-bands (Pew Research Center 2019a) and about 76% of people owning SPs (Pew Research Center 2019b). Bayindir and Paisley (2018) place these estimates even higher, putting smartwatch ownership (including smart-bends) at 24% and SPs ownership at 95%.

However, the use of these, now widely available and affordable technological tools, in scientific research is still in its infancy, with only a handful of studies using SPs as monitoring instruments (*see inter alia*, Dutta 2019; Martin et al. 2012). Most of these studies are carried out in laboratory conditions or in controlled laboratory settings (Gutierrez-Martinez et al. 2017; Machado et al. 2017; Murphy and King 2016; Odenwald 2020; Serpanos et al. 2018; Williams et al. 2017). This focus on laboratory testing effectively leaves the question open *whether SPs can be used in real-world conditions as sufficiently accurate ALAN and noise monitoring tools?* The present study aims to fill this knowledge gap.

In particular, to answer this question, we develop and use a standardized testing protocol, and employ the AndroSensor app, installed on three different popular and commonly used SPs, to perform measurements of ALAN and noise and to compare them with measurements performed by professional (Type 2) instruments. To the best of our knowledge, the present study is the first, which investigates the feasibility of using SPs for *simultaneous real-time monitoring of ALAN and noise in real-world conditions.*

Background studies

Modern SPs integrate a rich set of sensors, including high-resolution digital cameras, three-axis accelerometers, magnetometers, gyroscopes, global positioning devices (GPS), proximity sensors and others (Grossi 2019). These sensors are used to support SP functioning by monitoring the device's positioning, orientation and performance (Grossi 2019). By using different software apps, SPs' users can activate sensors and hardware components, such as ambient light sensor (ALS), microphone (MIC), pulse tracker, and many others. Using the algorithms embedded into the app, data collected from these apps can be stored in SP's memory or in the data cloud, projected on the hardware screen and analyzed (Yürür et al. 2016).

Studies, carried out in recent years, demonstrate the usefulness of SP technology for physical experiments (see *inter alia*, Hosker 2018; Salinas et al. 2018; Sans et al. 2013); biosensing (Dutta 2019); healthcare monitoring (Lesher et al. 2021), and infrastructure management (Alavi and Buttlar 2019). Constant improvement in materials, technology and software lead to a leap forward in SP sensing capabilities (Grossi 2019; Majumder and Deen 2019). This ongoing improvement makes past year technology quickly obsolete, as new, faster and improved devices are launched every year (Bai et al. 2018; Bayindir and Paisley 2018).

Studies, which investigate the performance of SPs as monitoring tools, are summarized in Table 1. As evidenced from this table, early studies note an impaired performance of the Android operating system (AOS), while Apple's iPhone operating system (iOS) is found to demonstrate better accuracy and consistency (Kardous and Shaw 2014; Murphy and King 2016; Williams et al. 2017). As technology evolves, AOS performance improved to a ± 1.6 dB error for measuring noise (Odenwald 2020), and to less than 1 dB after calibration (Ventura et al. 2017; Zamora et al. 2017). By adding an external MIC, Roberts et al. (2016) find that calibrated iOS can be used as a Type 2 Sound Level Meter (SLM). Garg et al. (2019) also demonstrate that AOS devices with an external MIC can be used, after calibration, as reasonably accurate noise monitoring tools.

Although studies, investigating the use of SPs for *noise measurements*, are on the rise, the use of such devices for *ALAN measurements* is still sporadic and infrequent (see Table 1), albeit several iOS and AOS apps, currently available, can make this task possible. These apps include the LightMeter app by WBPhoto (WBPhoto 2021), AndroSensor app by FivAsim (Fiv Asim 2015) and Physics Toolbox Sensor Suite app by the Vieyra Software (Vieyra Software 2021). To perform illumination measurements, these apps enable ALS, which is used to adjust the brightness of the phone in order to reduce the power consumption of the battery. If ALS operates, the screen of the phone become dim when it is dark, being sufficient enough to enable a user to see the phone's screen effectively (Dutta 2019).

Thus, in one of such studies, investigating the potential of SPs use for ALAN measurements, Gutierrez-Martinez et al. (2017) test the accuracy of AOS devices using a self-developed app, which enables the on-board camera, ALS and external light measurement kit. The researchers found that after applying a correction factor, the absolute error in illuminance measurements dropped to 6.35%

Table 1. Summary of studies in which SPs are used for light and sound monitoring.

Publication	Study type	Study setting and materials	Results	Limitations
(A) Sound measurements				
Kardous and Shaw (2014)	Laboratory	4 iOS and 5 AOS smartphones, 10 iOS and 4 AOS APPs. Reference device: Larson Davis model 831 Type 1 SLM for sound measurements in the acoustics chamber. Sound range: 65 to 95 dB, with a 5 dB increment.	SPLnFFT and SoundMeter APPs showed mean deviations of 0.07 dB (unweighted) and 0.52 dB (A-weighted) from the SLM values. NoiseHunter APP mean error was within ±2 dB. Conclusion: some APPs may suit occupational noise monitoring.	The study is based on an obsolete technology, not performed under field conditions and did not monitor low-level sounds of <65 dB.
Nast et al. (2014)	Laboratory	One iPhone 4s and 5 iOS APPs. Reference device: Brüel and Kjær Type 2250 Type 1 SLM. Special settings: acoustics chamber, with sound level varying from 4 to 95 dB in different combinations of sound pressure and frequency (125 Hz-4 kHz).	Most APPs erred by reporting higher sound levels (5–10 dB) than those measured by the professional equipment across all the frequencies tested. Pre-calibration and devices' dynamic range are found to be key factors for accuracy.	Obsolete technology; the study did not account for field conditions.
Kardous and Shaw (2016)	Laboratory	6 iPhone, 4 iOS APPs, i436 and iMM-6 Mics. Reference device: Larson Davis model 831 Type 1 SLM. Special settings: acoustics chamber; sound range: 65 to 95 dB, with a 5 dB increment.	The results showed ~ ±1 dB difference in measurements. As the authors of the study conclude, with Advances in APP design and external Mics, the gap in measurements between professional equipment and smartphone-based sensors is rapidly narrowing.	Obsolete technology; the study did not account for field conditions and low level sounds of <65 dB.
Roberts et al. (2016)	Laboratory	3 iPhone, 3 iOS APPs, and 3 iPods, i436 and iMM-6 external Mics. Reference device: Trident Multi-Chanel Acoustic Analyzer Software using a Larson Davis 2559 ½-in Mic. Special settings: acoustics chamber; sound range: 60 to 100 dB, with a 5 dB increment	In the first experiment, iPods internal Mic performed poorly. In the second experiment, when an external Mic was added, mean difference dropped to less <1 dB. External Mic coupled with smartphones may be used as a Type 2 measurement device.	-"-
Murphy and King (2016)	Laboratory	65 iOS and 35 AOS smartphones; 4 iOS and 3 AOS APPs. Reference device: calibrated Brüel & Kjær Type 2250 SLM. Special settings: acoustics chamber with initiated sound pulses of 27, 50, 70 and 90 dB.	The APPs performed well at 50 and 70 dB with mean difference of 2.09 and 1.33 dB respectively. Under a background noise (27 dB), the smartphones erred by 5.33 dB and at 90 dB. iOS performed better than AOS devices. As technology improves, APPs may play an important role in environmental noise monitoring.	Obsolete technology; the study did not account for field conditions.
Aumond et al. (2017)	Laboratory and field test	Step 1 – test devices: HTC One X, Samsung S3 and, Cart_ASUR AOS APP. Reference device: CEL-500 Type 1 SLM. Step 2 – calibrations and validation. Test devices: S.T: 8 HTC One X, Cart_ASUR APP, Reference device: G.R.A. S. MCE 212 Type 1 Mic. Special settings for step 1 and 2: acoustics chamber; sound range 35 to 100 dB, with a 5 dB increment. Step 3: one year long field test. Test devices 60 HTC one X, Cart_ASUR APP. Ref: RION NL52 Type 1 SLM. Special settings: two Ladybird (Azimut Monitoring) fixed monitoring stations.	Step 1: HTC One X showed a good sensitivity in the 35–100 dB(A) range. Step 2: the 7 smartphones behaved similarly and linearly in the range between 50 and 90 dB(A). Systematic mean errors correction was applied. Accuracy issue under 50 dB(A) and greater than 90 dB(A) was overlooked as in urban areas, sound levels are most likely to be in the 50–90 dB range. Step 3: A strong correlation was observed between the three measurement systems for both locations (r > 0.9).	Obsolete technology with data colleting and measurements took place between 2013 and 2014.
Ventura et al. (2017)	Indoor and field test	15 AOS smartphone with AmbiCiti APP. Reference device: Cirrus Optimus red Type 1 SLM. Special settings: carpeting, and partially padded room with absorbent material; total room area – about 30 m^2 with 60 m^2 wall surface. Sound range: 40 to 95 dB, with a 5 dB increments	The average bias is found to span in a large range: from −32.5 to 6.9 dB (A-weighted), with a large majority of negative values. The overall average is −11.3 dB (A-weighted). A validity test after calibration revealed discrepancies to be relatively small for all tested devices <1 dB (A-weighted).	Most of the tested smartphone devices are now obsolete.

(*Continued*)

Table 1. (Continued).

Publication	Study type	Study setting and materials	Results	Limitations
Williams et al. (2017)	Laboratory and field test	Step 1: 2 iOS and 3 AOS smartphones, Setting: Laboratory Waveform (WAV) testing for best performing device. Step 2 – Laboratory verification: iPhone 5, with self-develop APP. Reference device: B&K model 2250 SLM type 1 Sound range: 40 to 120 dB (1–4 kHz), with increments not specified. Step 3 – field verification: iPhone 5, with a self-develop APP. Reference device: B&K model 2250 SLM type 1(>30 min tests), model 350 and 35X, dosimeters (under 30 min tests).	Step 1: iOS was found to have a better consistency and repeatability than AOS-based smartphones. Step 2: a strong linear correlation ($P < .02$) was established between the iOS APP and SLM. Step 3: a linear strong correlation ($P = .03$) was established between the iOS APP and references devices. However, windy conditions decreased iOS Mic performance and saturation effect was found at high peak levels (>120 dB, $R^2 = 0.91$). The results are found to be acceptable for risk management practice but not for detailed assessments	Most of the tested S.T are obsolete. The study is based on specific algorithm for acoustics analysis not available as *off the shelf* APPs. Field sample included 72 measurements.
Zamora et al. (2017)	Laboratory and field test	Step 1 – calibration: Samsung S7; 3 sound analysis algorithms. Reference device: PCE-322A type 2 SLM and type 1 SLM (model was not specified) Step 2 – Laboratory validation: 4 Samsung models. Reference device: PCE-322A type 2 SLM. Special settings in Stepa 1 and 2: acoustics chamber; sound range 35 to 95 dB, with a 10 dB increment under different sampling rates and buffer size. Step 3 – field validation test: Samsung S7. Reference device: SLM model is not specified.	Step 1: Less than 4% mean estimation error, best results in sampling rates analysis and block analysis. Step 2: Each model performed differently but by applying an adjusted value using linear regression the error dropped <1% in most cases. Step 3: In all cases the mean error was <0.0308%. Both sampling rate and selected buffer size significantly impact the accuracy of noise level estimations. As the authors argue, it is possible to accurately assess noise levels by taking relatively short samples (from 1 to 3 s) while introducing a minimal estimation error,	The study is based on specific algorithm for acoustics analysis not available as *off-the-shelf* APPs.
Serpanos et al. (2018)	Laboratory and indoor field test	iPhone 6S, 3 iOS APP's – Analyzer, Sound Level Meter Pro and SPL Meter with and without calibration Reference device: Bruel & Kjaer, 2250 Type 1 SLM. Step 1 – Laboratory assessments. Special settings: acoustics chamber with sound range between 20 and 100 dB, with a 10 dB increment. Step 2 – indoor field assessments. Special settings: 8 clinical unoccupied rooms in private schools during school hours. Sound range (measured): 28.2 to 40.4 dB.	Step 1: after calibration Analyzer was found to be accurate (± 2 dB) in the entire 50 to 100 dB range, while Sound Level Meter Pro and SPLMeter showed good results only at low noise levels, 40 to 100 dB ($p < .05$). Step 2: APPs' ambient noise measures were inaccurate. Overestimations were greater for APPs without calibration (~3 to 19 dB) in compared to APPs with calibration (~3 to 10 dB). The authors conclude that APPs with calibration may be used to accurately record sound measures of above 40 dB, at least in a sound-treated environment.	Field conditions were limited to low sound intensities and heavily controlled. Only one type of smartphone was tested in the study.
Garg et al. (2019)	Field test	Two Galaxy S4, one Galaxy S7 and one ZTE Blade Q Pro smartphone, with self-developed NoiseExplorer APP. Reference device: PCB 377B02 class 1 Mic with B&K Sonoscout Type 3663 data recording system Settings: sound recording in different environments.	After calibration, 99.7% of the measurements have an error within ±0.7 dB for S4 and 7 while the ZTE Blade Q Pro error was within ±2.1 dB. By using phone model, generic, calibration file different devices of the same models had been calibrated successfully (meant error of −0.2, ±0.3 dB). High-end devices sowed better performance.	The study is based on specific algorithm for acoustics analysis not available as *off the shelf* APPs. This method requires an external Mic.

(*Continued*)

Table 1. (Continued).

Publication	Study type	Study setting and materials	Results	Limitations
(B) Light measurements				
Gutierrez-Martinez et al. (2017)	Laboratory	Test device: PCE-174 (PCE Iberia, Tobarra, Spain). Special settings: Dark room with no external light, light bulb with a dimmer; Light range between 0 to 700 LX. Step 1 – ALS performance LG Nexus 5 smartphone, self-developed APP. Step 2 – Smartphone camera testing: Sony Xperia M2 smartphone, self-developed APP. Step 3 – external device: Alcalux LM,	Step 1: During pre-calibration, 39.08% absolute error was established; after post-calibration the absolute error dropped to 8.41%. Sony Xperia M2 and a BQ Aquaris X5 were used for validation; the absolute error was 7.80% and 9.58% respectively. Step 2: Before calibration, the absolute error was 12.63%, after calibration the absolute error dropped to 6.35%. LG Nexus 5 and a BQ Aquaris X5 used for validation, after calibration error was reduced by 5.67% and 2.15% respectively. Step 3: Absolute error was 2.7%. The authors conclude that smartphones can be used as light measurement sensors when high precision data are not required.	Most of the tested smartphones are now obsolete. The study is based on specific algorithm for LM using self-developed APPs not available as *off the shelf* APPs. The study is carried out in controlled, laboratory conditions.
Machado et al. (2017)	Laboratory	Test device: Moto G XT1068, with a self-developed APP (name not specified). Reference device: HDE® LX-1010B LM. Special settings: Dark room with no external light, fluorescent light with a dimmer. Light range: 50 to 1000 LX, with a 50 lx increments.	No significant difference between smartphone measurements and lux-meter measurements ($p < .05$) with mean difference <0.1 LX. The authors conclude that the tested smartphone has enough accuracy to perform light measurement in laryngoscopes light.	Only one type of smartphone was tested in controlled laboratory conditions.
(C) Sound and light measurements				
Odenwald (2020)	Laboratory and field-controlled conditions	Test devices: Samsung Note 5 and Samsung S8 with Lux Light Meter APP by Doggo and Light Meter by WBPhoto for light, iPhone 6S with Galactica APP by Flint; Light Meter by Vlad Polyansky and Light Meter by Elena Polyanskaya for light. For noise Decibel 10th APP by SkyPaw Co. Ltd. Reference device: For light – LT-300 and Sekonic C-7000 both type 1 LM. For sound – B&K Precision Model 732A Sound Level Meter type 2 SLM Special settings: For light – smartphones back camera measured albedo from a white foam surface placed outside. For sound outdoor was recorded using the APP, a quiet chamber was used to compare and pre-calibrate the smartphones.	Light: pre-calibration measurements error exceeds 150%, after calibration error range dropped 12–18% depending on illumines range (high-to-low). Noise: pre-calibration smartphones had poor performance with an offset of −12 dB for note 5, 5 dB for S8 and −8 dB for iPhone 6S. after calibration the accuracy improved to ±1.6 and ±3.3 dB. The authors conclude that light intensity can be measured after calibration with an accuracy of ±12% under high-illuminance conditions but there is significantly worse performance below 3,000 LX. Sound measurements have a random noise component of approximately ±1.5 dB. When proper calibrated, smartphone sensors can generate good-quality data that compare reasonably well with professional-grade systems, but at far lower cost.	Mostly controlled conditions. No standardized protocol, with different APPs and conditions set to measure light and sound.

(from 12.63% before correction) and to 2.7%, when the external light measuring kit is used. In a separate study, Machado et al. (2017) found no significant differences between AOS ALS measurements and by the measurements performed using an HDE® LX-1010B type luxmeter with the average error of less than 0.1 lux ($p < .05$). Yet, Odenwald (2020) reports a 12%-18% average error, after comparing measurements performed using iOS and AOS apps with professional grade light measurement equipment.

However, it should be noted that most attempts to validate SPs as ALAN and noise measurement instruments have been performed under controlled, i.e., close to laboratory conditions (Odenwald 2020; Serpanos et al. 2018). Other studies were based on a small number of measurements (Williams et al. 2017), or used *ad hoc* algorithms, embedded in self-developed apps (Garg et al. 2019; Williams et al. 2017; Zamora et al. 2017). As a result, these studies lack generality, and their results cannot be replicated in wide-scale real-world experiments. The present study attempts to address these issues by applying a standardized, yet simple methodological approach, applying it to a variety of real-world conditions, as detailed in the next subsections of this paper.

Research method

Research protocol

To verify a possibility that reliable information on noise and ALAN exposure measurements can be obtained from SPs sensors, we devised a standardized test protocol, featuring different combinations of ALAN and noise level settings in bedrooms and living rooms of typical urban apartments that face busy city streets.

The sources of ALAN and noise in residential apartments are diverse, as these types of environmental pollution come from both *outdoor* emitters (such as car engines and headlights, streetlights, AC compressor and others) and from *indoor* devices, such as TVs, room lights, household appliances and so on. In addition, apartments' residents can change the level of exposure to ALAN and noise by opening or closing windows, or/and raising or lowering window shutters. Therefore, while devising the study protocol, we considered a combination of several factors, as detailed in Table 2: computer screen (on/off), TV (on/off), background light (15 W LED, on/off), windows (open/closed) and shades (open or lowered). The combinations of these factors defined in Table 2 are assumed to reflect a variety of settings that might occur in apartments at night.

To perform the measurements, under each combination of the above-mentioned factors, we placed the tested SPs (see Table 3) on a flat horizontal platform in the middle of the room, with the sensors directed to the largest source of light, in order to account for ALS location inside the SPs (Gutierrez-Martinez et al. 2017). Next to the SPs tested, we positioned measurement instruments – SL-814 for sound measurements and LX-1330B for ALAN measurements.

The measurements were performed from late February to the end of March 2021, when *no* space cooling or heating is normally required in Israel, which we considered important to minimize the potential impact of artificial wind sources, such as air conditioners and fans, on the instruments.

During 23 consecutive nights, between 19:00 to 23:00, ALAN and sound measurements collected from all devices every 5 minutes. The measurement process resulted in 1,150 observations for each device for ALAN and sound, separately, thus totaling 3,450 measurements for all three SPs, matched by the same number of simultaneous measurements by the control instruments.

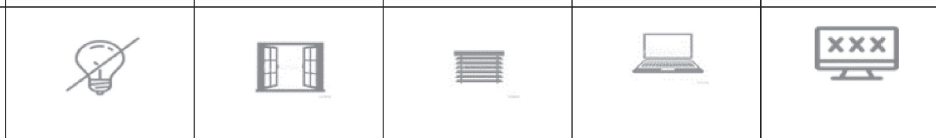
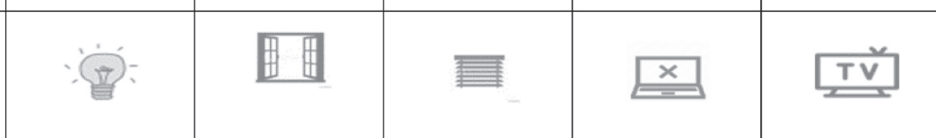
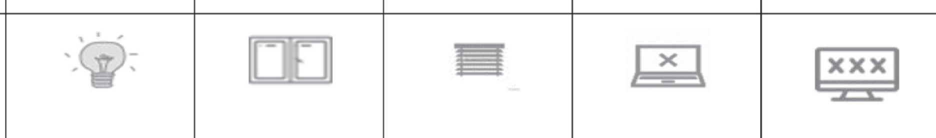
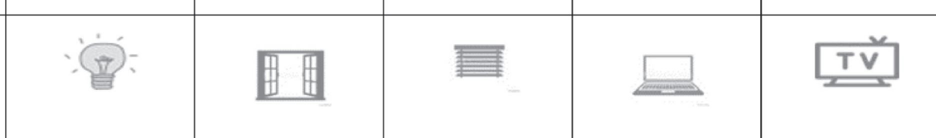
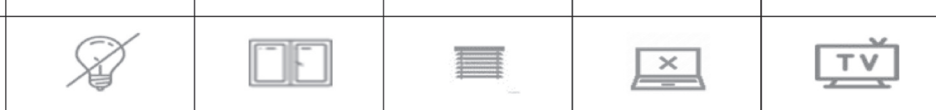
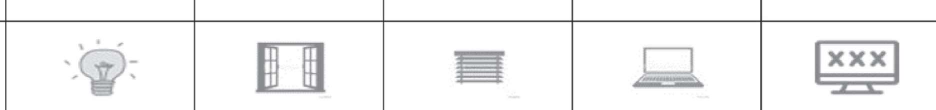
Measurement locations

Measurements were taken in two different locations in Israel: The City of Nahariya (68,988 residents) and the City of Tamra (35,210 residents) (Gov Data 2021); see Figure 1. The cities in question are major cities in northern Israel, characterized by dense development patterns and relatively high traffic volumes. While the City of Nahariya has predominantly Jewish population, the City of Tamra is an Arab town. Although differences in ethnicity are not analyzed in this study *per se*, we consider that representing ethnically different places might be important for investigating differences in exposure between different groups of localities in the future. In both cities, the test apartments, in which the measurements were performed (one in each city), are located on main streets: near the Tamars Mosque in Tamra and next to the Yitzhak Sadeh St. in Nahariya (see Figure 2).

SPs, apps and control devices

Three different Samsung SPs – Galaxy A5-SM520F, Galaxy s7 and Galaxy S20FE5G – were used in the study as test devices (see Table 3). Samsung SPs are very popular in Israel, as elsewhere, forming ~48% of the domestic SPs market (GlobalStats 2021). The market proliferation was an important consideration for selecting the test devices, considering their potential use in future experiments. All the SPs used in the test run on the Android Operating System (AOS) but were released to the market in different years and incorporate

Table 2. Measurement protocol.

Measurement code	Measurement settings				
	Light	Windows	Shades	PC	TV
M1					
M2					
M3					
M4					
M5					
M6					
M7					
M8					
M9					
M10					
M11					
M12					

(*Continued*)

Table 2. (Continued).

Measurement code	Measurement settings				
	Light	**Windows**	**Shades**	**PC**	**TV**
M13	lights on	windows closed	shades open	PC on	TV off
M14	lights on	windows open	shades open	PC off	TV off
M15	lights on	windows closed	shades closed	PC on	TV on
M16	lights on	windows closed	shades closed	PC on	TV off
M17	lights on	windows open	shades closed	PC off	TV on
M18	lights on	windows open	shades closed	PC off	TV off
M19	lights off	windows closed	shades open	PC on	TV on
M20	lights on	windows closed	shades open	PC off	TV on
M21	lights off	windows open	shades open	PC off	TV off
M22	lights off	windows open	shades closed	PC off	TV off
M23	lights off	windows closed	shades open	PC off	TV off

Notes: lights off; lights on; windows closed; windows open; shades closed; shades open; PC off; PC on; TV off; TV on

somewhat different features, as detailed in Table 3. In particular, the first SPs – Samsung Galaxy A5-SM520F – were released in 2017 and incorporates two microphones (top and bottom) with active noise canceling, and has an ALS featuring maximum measurement range of up to 60,000 lx with a 1 lx resolution (GSMArena team 2017). The Galaxy S7 SPs, released in 2016, have similar features: it incorporates two high hand microphones (top and bottom) with active noise canceling (Zamora et al. 2017) and its TMS49XX ALS has the maximum measuring range of 60,000 lx with a 1 lx resolution (Boycracked 2016). Concurrently, Samsung

Table 3. Mobile phones used in the study and their basic characteristics.

	Phone 1	Phone 2	Phone 3
Manufacturer	Samsung	Samsung	Samsung
Brand	Galaxy A5-SM520F	Galaxy S7	Galaxy S20FE5G
Image			
Release year	January 2017	March 2016	October 2020
Dimensions (LxWxH)	146.1 x 71.4 × 7.9 mm mm	142.4 x 69.6 × 7.9 mm	159.8 x 74.5 × 8.4 mm
Network Technology	GSM/HSPA/LTE	GSM/HSPA/LTE	GSM/CDMA/HSPA/EVDO/LTE/5 G
OS	Android 6.0.1 (Marshmallow), upgradable to Android 8.0 (Oreo)	Android 6.0 (Marshmallow), upgradable to Android 8.0 (Oreo), TouchWiz UI	Android 10, upgradable to Android 11, One UI 3.1
Chipset	Exynos 7880 (14 nm)	Exynos 8890 Octa (14 nm)	Qualcomm SM8250 Snapdragon 865 5 G (7 nm+)
CPU	Octa-core 1.9 GHz Cortex-A53	Octa-core (4x2.3 GHz Mongoose & 4 × 1.6 GHz Cortex-A53)	Octa-core (1x2.84 GHz Kryo 585 & 3 × 2.42 GHz Kryo 585 & 4 × 1.8 GHz Kryo 585)
WLAN	Wi-Fi 802.11 a/b/g/n/ac, dual-band, Wi-Fi Direct, hotspot	Wi-Fi 802.11 a/b/g/n/ac, dual-band, Wi-Fi Direct, hotspot	Wi-Fi 802.11 a/b/g/n/ac/6, dual-band, Wi-Fi Direct, hotspot
Internal memory	32GB 3GB RAM	64GB 4GB RAM	128GB 8GB RAM,
Main camera	16 MP, f/1.9, 27 mm (wide), AF	12 MP, f/1.7, 26 mm (wide), 1/2.55″, 1.4 µm, Dual Pixel PDAF, OIS	12 MP, f/1.8, 26 mm (wide), 1/1.76″, 1.8 µm, Dual Pixel PDAF, OIS8 MP, f/2.4, 76 mm (telephoto), 1/4.5″, 1.0 µm, PDAF, OIS, 3x optical zoom12 MP, f/2.2, 13 mm, 123° (ultrawide), 1/3.0″, 1.12 µm
Selfie camera	16 MP, f/1.9, 26 mm (wide), 1/3.06″, 1.0 µm	5 MP, f/1.7, 22 mm (wide), 1/4.1″, 1.34 µm	32 MP, f/2.2, 26 mm (wide), 1/2.74″, 0.8 µm
ALS	TMD3725 0–60000, 1 LX resolution	TMS49XX 0–60000 LX, 1 LX resolution	Stk31610 0–4095.96 LX, 0.53 LX resolution
Microphone	2 mics with active noise canceling	2 mics with active noise canceling	2 mics with active noise canceling
Battery	Li-Ion 3000 mAh, non-removable	Li-Ion 3000 mAh, non-removable	Li-Ion 4500 mAh, non-removable
Price (as of April 2021)	350 US$	252 US$	785US$
Source	GSMArena team (2017)	Boycracked (2016)	GSMArena team (2020)

Figure 1. Location of the study sites (ArcGIS 2015).

Galaxy S20FE5G SPs, released in 2020, incorporate two high hand microphones (top and bottom) with active noise canceling and Stk31610 ALS featuring maximum measuring range of 4,094 lx with 0.53 lx resolution (GSMArena team 2020).

On all SPs tested, the AndroSensor App by Five Asim was installed. The app in question is freely downloadable from the Google© Play Store and offers an easy-to-use interface with multi-sensor logging capabilities (Fiv Asim 2012) The app generates an *.csv* output file automatically and enables emailing the data collected from all active sensors, according to a predefined measurement frequency.

The ALAN reference device was LX-1330B, manufactured by Dr. Meter with light intensity threshold of 0.1 to 200,000 lx, 0.1 lx resolution, and ±2% repeatable accuracy (DrMeter 2019). The device used for noise measurements – SL-814 – is manufactured by Oaktree-Products and is fully compliant with IEC651 & ANSI S1.4, with a measurement range of 30 to 130 dB with a 0.1 dB resolution (Oaktree Products 2013).

Data analysis

The measurements assembled from SPs and controlled instruments were cointegrated and imported into the IBM SPSS 26.0^{TM} software for analysis. The analysis was performed in the following two stages: First, we mutually compared the measurements collected by SPs and reference instruments, using scatterplots, generated for noise and ALAN separately. Next, correlation coefficients were estimated and trend lines were fitted and analyzed.

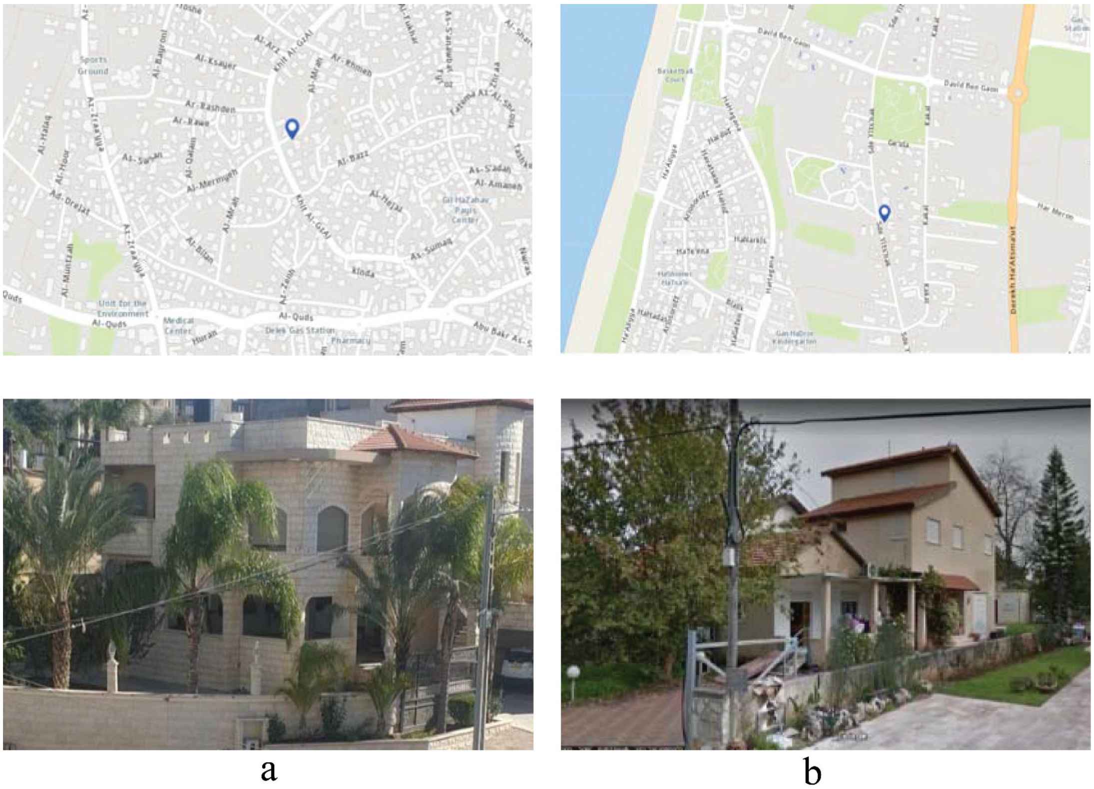


Figure 2. Location and pictures of building in which the measurements were carried out: A. Khalet el-Ghazal st, Tamara (Google, n.d.a), B. Yitzhak Sadeh St., Nahariya (Google, n.d.b).

Research hypothesis

Several previous studies investigated the accuracy of SPs as measurement instruments (see Table 1). However, as previously mentioned, most of these tests were performed in controlled or close-to-laboratory conditions. It thus remains unclear whether SPs measurements are sufficient accurate in real-world field studies, in which the exposure might occur under different combinations of ambient factors. Therefore, our operational research hypothesis was formulated as follows:

H_0: The accuracy of ST devices for ALAN and noise measurements in real-world conditions is insufficient and such measurements cannot be used as supporting evidence for scientific research.

H_1: Light and sound sensors, installed on common SPs devices, provide sufficiently accurate measurements of ALAN and noise exposure, thus making them a sufficiently accurate tool for investigating ALAN and noise exposures in real-world experiments.

If this hypothesis is correct, then we shall see a strong and linear association between measurements performed by reference instruments and SPs' apps (r = 0.9 or more, $p < .01$). Otherwise, we should reject this hypothesis.

The research conforms to the international ethical standards for biological rhythm research studies (Portaluppi et al. 2010).

Results

In Table 4, we report descriptive statistics of the measurements performed by different SPs, for ALAN and noise separately. As evidenced by this table, the standardized mean error for ALAN varies between 0.026–0.064 (2.6%-6.4%), with Samsung S7 providing most accurate results (standardized mean error = 0.026 (2.6%); SD = 1.35). For noise measurements, standardized mean errors reach 0.157 (15.7%), SD = 3.65 for Samsung A5; 0.135 (13.5%), SD = 4.99 for Samsung S20FE5G, and 0.064 (6.4%), SD = 2.97 for Samsung S7.

The results of the mutual comparison of ALAN and noise measurements by the test SPs and control instruments are reported in Figure 3. As evidenced by this

Table 4. Descriptive statistics of the research variables.

Measurement type and statistic	Measurement location: Tamra[a]	Nahariya[b]	
	Mobile phone brand		
	Samsung A5	Samsung S7	Samsung S20FE5G
(A) Measurements performed by smartphones			
Noise, dB			
• Min	12	39	34
• Max	61	74	87
• Mean	34.16	46.01	46.87
• Standardized absolute mean error[c]	0.157	0.064	0.135
• SD[d]	3.65	2.97	4.99
• No of obs.	1150	1150	1150
ALAN, lx			
• Min	0.00	2.00	2.00
• Max	194	101	102
• Mean	59.20	46.90	46.04
• Standardized absolute mean error[c]	0.064	0.026	0.027
• SD[d]	4.39	1.35	1.43
• No of obs.	1150	1150	1150
(B) Measurements performed by instruments			
Noise – SL814 (dB)			
• Min	20	39	
• Max	70	78	
• Mean	40.47	43.89	
• SD	10.63	4.04	
• No of obs.	1150	1150	
ALAN – LX-1330B (lx)			
• Min	1	2	
• Max	205	103	
• Mean	62.99	46.83	
• SD	70.25	35.81	
• No of obs.	1150	1150	

Notes: [a] Khalet el-Ghazal st'; Tamara, [b]Yitzhak Sadeh st., Nahariya (see Figures 1–2); [c] Standardized absolute mean error between measurements performed by reference instruments (SL814 and LX-1330b) and SPs; [d] Standard Deviation for the calculated error.

figure, the correlation between the measurements performed by the control device and SPs measurements is very high for ALAN (r = 0.998–0.999) and much lower for noise (r = 0.76–0.94).

Among the test devices, Samsung A5-SM520F reports the highest correlation for *noise* measurements ($r = 0.94$, $p < .01$), as opposed to Samsung S7 ($r = 0.83$, $p < .01$). Somewhat surprisingly, the lowest correlation for noise is observed for the newest Samsung S20FE5G SPs ($r = 0.76$, $p < .01$); see Table 5. Characteristically, in all cases, the shape of the trend lines is close to linear, with their slope approaching 45° for Samsung A5-SM520F, ~40° for Samsung S7 and ~30° for Samsung S20FE5G. This indicates that the latter two SPs tend to underestimate the levels of noise exposure and might thus require the application of a correction factor, if used for measurements.

Concurrently, for ALAN, the measurements from all the test SPs are found to be quite accurate, being almost identical to the measurements performed by the control instrument ($R^2 = 0.998–0.999$; $p < .01$), with the shape of the trend lines being close to straight lines with a 45° slope for all test devices.

As previously mentioned in the research protocol section, while designing the experiment, we followed the recommendations of Gutierrez-Martinez et al. (2017) and Sans et al. (2017), according to which the tested SP is placed toward the strongest source of light, so as to minimize a measurement bias potentially attributed to the location of the ALS in the SP. Yet, in order to assure that the test results are not solely affected by major luminaries located on the ceiling or other major sources of lighting, we analyzed the test results separately for different room settings, both with and without a dominant luminary. The results of such a stratified analysis are reported in Figure 4, which shows that SP measurements and measurements by control instruments correlate strongly for both types of room settings, that is, for room settings with *and* without major luminaries ($R^2 = 0.912–0.999$).

Discussion

Light pollution affects a variety of processes in natural ecosystems, affecting animal reproduction system, predator-prey relationship, and competition of species (Gaston et al. 2013; Svechkina et al. 2020). In humans, excessive exposure to ALAN is also known to be linked to various illnesses and health disorders, such as breast cancer (Blask et al. 2005; Garcia-Saenz et al. 2018; Hurley et al. 2014; Kloog et al. 2008, 2011, 2010), prostate cancer (Garcia-

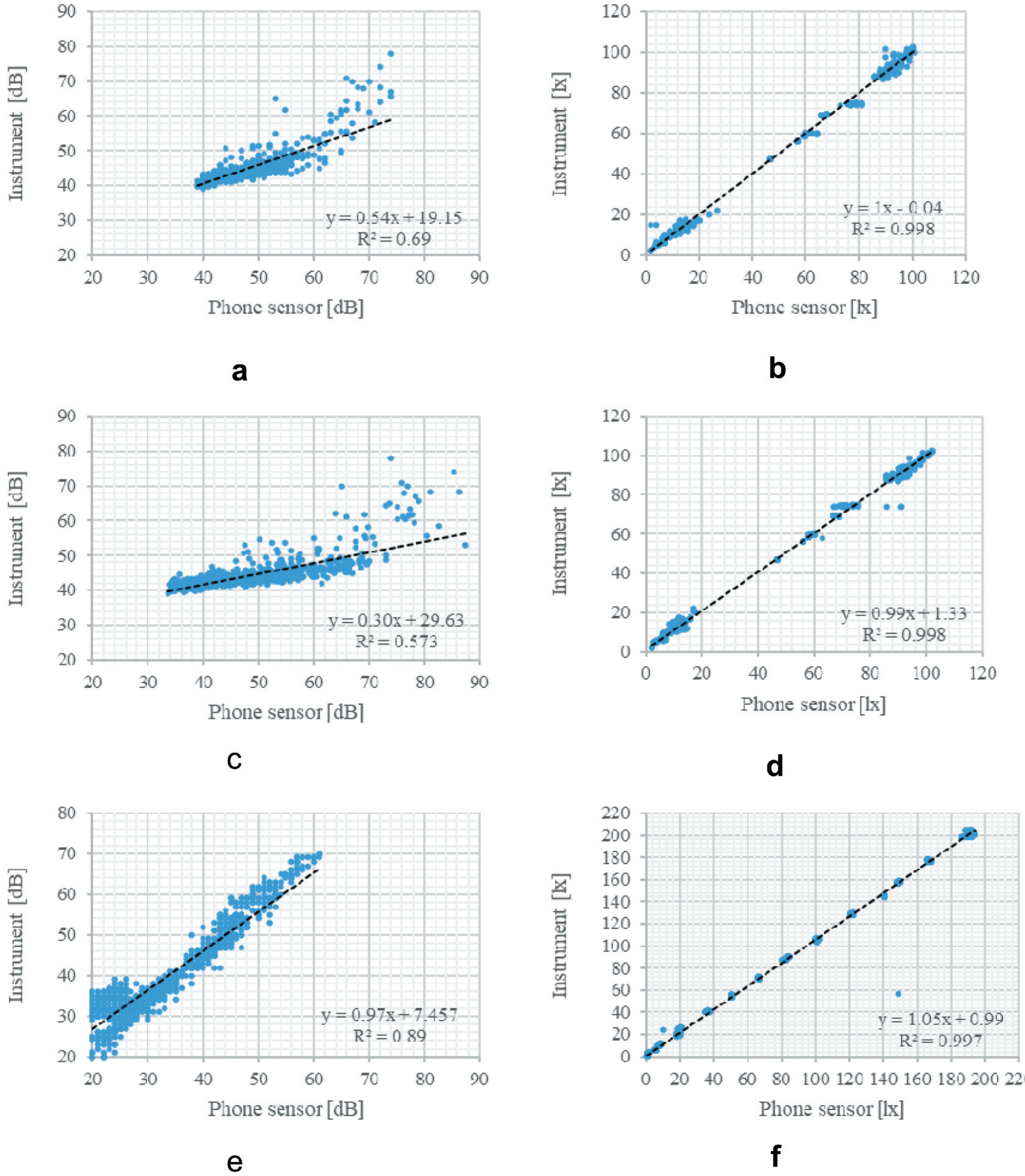


Figure 3. Comparison of noise and ALAN measurements, performed by different SPs with measurements performed by noise and light measurement instruments (see text for explanations). *Notes*: Left panel diagrams – Noise measurements; right panel diagrams – ALAN measurements; A, B – Samsung Galaxy S7; C, D – Samsung Galaxy S20FE; E, F – Samsung Galaxy A5; Instruments used for measurements: SL814 for sound and LX-1330B for light.

Table 5. Pearson correlation for SPs with control devices.

Pearson correlation coefficient by measurement type	Mobile phone brand		
	Samsung A5	Samsung S7	Samsung S20FE5G
r_{ALAN}	0.998**	0.999**	0.999**
r_{noise}	0.94**	0.83**	0.76**

Notes: * Indicates a 0.05 significance level; ** Indicates a 0.01 significance level

Saenz et al. 2018; Kloog et al. 2009), obesity (Rybnikova et al. 2016), fatigue (Martin et al. 2012) and sleep quality (Dijk and Archer 2009; Gabinet and Portnov 2021; Smolensky et al. 2015). The known mechanism behind such associations includes circadian disruption (Cho et al. 2013; Zeitzer et al. 2000, 2005) and reduction in melatonin (MLT) secretion (Chellappa et al. 2013; Wahnschaffe et al. 2013; Zubidat and Haim 2017), as well as general stress, attributed to ALAN exposure (Haim and Portnov 2013).

Noise is another environmental risk factors, exposure to which is known to be a source of annoyance (Åhrlin 1988; Bolin et al. 2011; Fields and Walker 1982; Öhrström et al. 1980; Taylor 1982); bad mood,

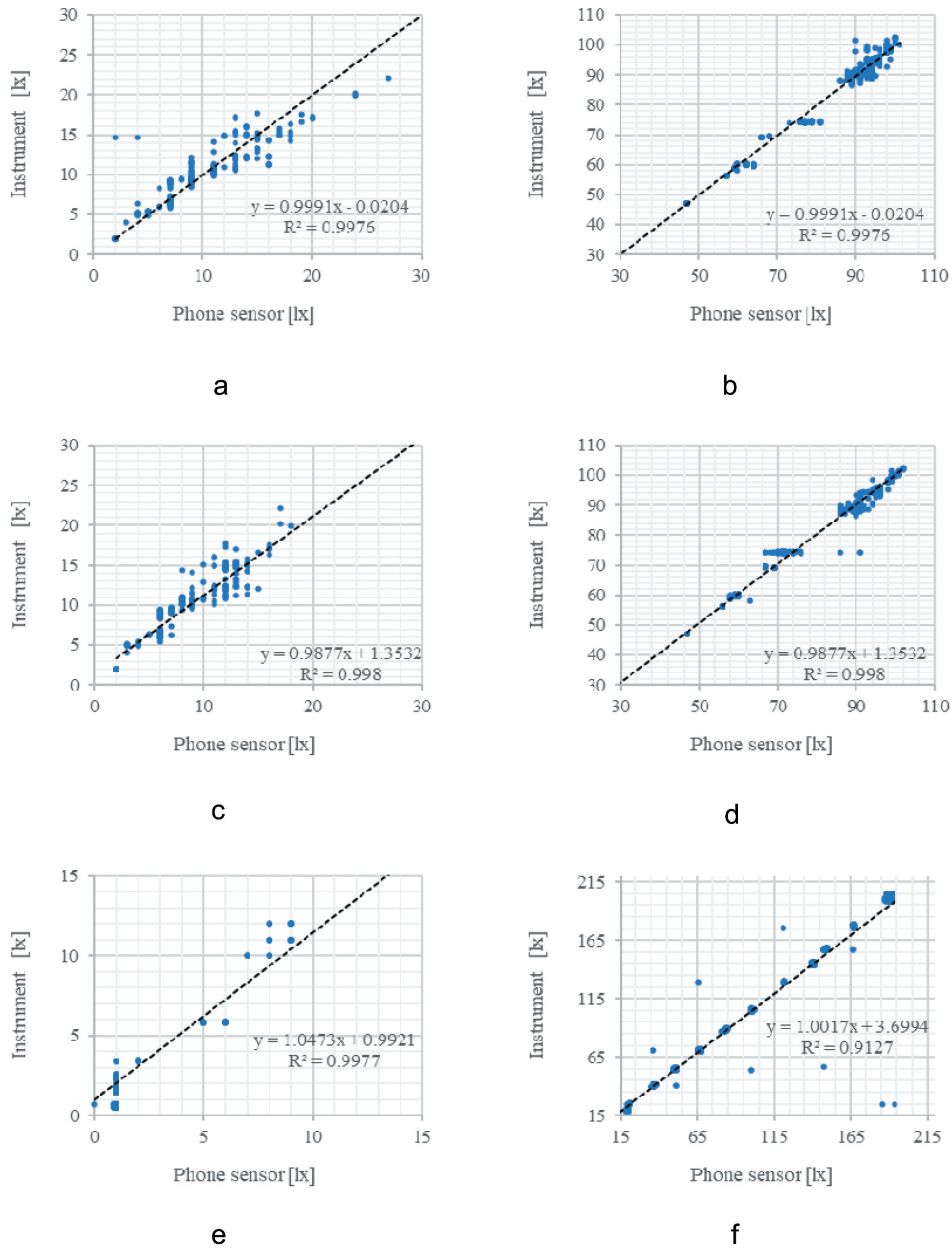


Figure 4. Comparison of measurements performed by SPs with measurements performed by light measurement instruments under different ALAN settings. *Notes*: A, C, E (left-panel diagrams) – room lights off (Measurement codes: M1, M2, M4, M6, M9, M11, M19, and M21-M23; see Table 2); B, D, F (right panel diagrams) – room lights off (measurement codes: M3, M5, M7-M8, M10, M12-M18, M20; see Table 2); SP devices: A, B – Samsung Galaxy S7; C, D – Samsung Galaxy S20FE; E, F – Samsung Galaxy A5.

depression, reduced cognitive performance (Carter 1996; Öhrström 1991; Waye et al. 2003; Wilkinson 1963) and various physiological responses, including hearing loss (Lewis et al. 2013; Lim et al. 2017), stress (Babisch et al. 2001; Ising and Braun 2000; Maschke et al. 2002; Waye et al. 2003), sleep disturbance (Basner et al. 2011; Berg 2001; Buxton et al. 2011; Eberhardt et al. 1987; Freedman et al. 2001; Griefahn et al. 2008; Jakovljević et al. 2006; Okada and Inaba 1990; Passchier-Vermeer 2003; Smith et al. 2013; Stanchina et al. 2005;

Topf 1992; Vallet et al. 1983) and increase in the risk of ischemic heart disease (Carter et al. 1994; Van Kempen et al. 2006).

A possible reason for a relative scarcity of *individual-level studies*, investigating the effect of noise and ALAN on human and ecosystem health, may be attributed to technical difficulties associated with using expensive and bulky monitoring equipment for field measurements, which impede large-scale experiments (Pueh et al. 2018; Zamora et al. 2017). This limitation also impedes citizen science initiatives aimed at integrating data, collected by volunteers for scientific research and for formulating public policies, also known as *bio-science* (Guerrini et al. 2018; Irwin 2001).

A potential alternative to the use of laboratory equipment for ALAN and noise measurements is SPs' measurements, which accuracy is investigated in this study. At present, SPs incorporate a variety of sensors, including high-resolution digital cameras, three-axis accelerometers, magnetometers, gyroscopes, GPS, proximity sensors, ALS, MIC, pulse tracker and others (Grossi 2019). Modern SPs constantly improve in performance and quality and are widely available and affordable (Mallinson 2015). This presents an opportunity for using such devices in wide-scale exposure monitoring, providing, of course, that their measurements are sufficiently accurate.

To verify the accuracy of common SPs as ALAN and noise measurement tools, the present study employed a standardized testing protocol, representing different room settings. The collected data were then analyzed, to estimate the correlation between SPs measurements and measurements performed by control instruments.

The analysis of 3450 measurements, performed in two different locations in Israel, reveal that SPs measurements and measurements performed by control instruments correlate strongly for noise ($r = 0.76–0.94$) and are nearly identical for ALAN ($r = 0.998–0.999$). The association between the two types of measurements is also found to be close to linear, with the slope of the trend lines being close to 45° for ALAN and varying between 30° and 45° for noise, depending on the SPs used.

Several limitations of this study are to be mentioned. First and foremost, the study was based on measurements performed using three SPs only, all of which ran on AOS. The study also used one app – AndroSensor. Although the SPs we tested are proliferate, which we consider important for future wide-scale experiments, we cannot exclude a possibility that somewhat different results might have been obtained if iOS, or other monitoring apps were used. Therefore, follow up studies should consider using the test protocol we developed to test a larger variety of AOS and iOS SPs and/or other monitoring apps available in the market, such as Physics Toolbox Suite by Vieyra software (Vieyra 2018; Vieyra Software 2021) or others. As the present study was carried out in two apartments only, follow up studies should also expand the number of testing sites and their geographic settings.

It should also be noted that we measured ALAN and sound intensities but did not account for ALAN and sound spectra. As well established, different spectrum combination of light and noise may have different effects on human health and wellbeing (see *inter alia*, Bolin et al. 2011; Chellappa et al. 2013; Van Kamp et al. 2017; Van Kamp and Van Den Berg 2018; Wahnschaffe et al. 2013; Waye et al. 2003). Therefore, follow up studies should account for spectral power distribution of ALAN and noise, using specialized apps, such as, Light Analyzer by Open-Source Physics Singapore (Open Source Physics Singapore 2019) or Spectroid app by Carl-Reinke (Reinke 2018).

Conclusions

The importance of ALAN and noise measurements for large-scale chronobiological studies, carried out in real-world conditions, is due to potentially adverse effects of these environmental risk factors on human morbidity, attributed, *inter alia*, to MLT suppression, general stress and circadian disruption (Haim and Portnov 2013). The effects of these environmental risk factors on ecosystem health are also substantial (Slabbekoorn 2019; Svechkina et al. 2020). However, the use of bulky and often expensive laboratory equipment for monitoring these environmental risk factors, especially in large scale real-world experiments, is not always feasible. Therefore, in this study we tested a possibility of using widely available SPs for ALAN and noise monitoring, which might facilitate future large-scale individual-level studies of biological rhythms, to be carried out in real-world conditions.

Our main conclusion is that the level of accuracy of ALAN measurements by SPs is greater for ALAN than for noise, which can make SPs a useful tool for large-scale ALAN studies that do not require the accuracy of professional (Type 1 or Type 2) instruments. In this respect, the standardized testing protocol developed in this study can offers an easy-to-follow approach for calibrating any SPs in real-world conditions. To the best of our knowledge, the present study is the first which developed such a protocol and tested it empirically. However, follow up studies should test the accuracy of different AOS and iOS using other APPs available, with emphasis on spectrum power distribution and extending the sample of cities with respect to demographical, socioeconomical and environmental heterogeneity which needs to be accounted for.

Funding

The study was supported in part by the estate of Ernest Petrie.

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References

Åhrlin U. 1988. Activity disturbances caused by different environmental noises. J Sound Vib. 127:599–603. doi:10.1016/0022-460X(88)90389-6

Alavi AH, Buttlar WG. 2019. An overview of smartphone technology for citizen-centered, real-time and scalable civil infrastructure monitoring. Futur Gener Comput Syst. 93:651–672. doi:10.1016/j.future.2018.10.059

ArcGIS. 2015. National geographic world map. [accessed 2021 May 4] https://www.arcgis.com/home/item.html?id=b9b1b422198944fbbd5250b3241691b6.

Asim F. 2012. AndroSensor for Android. [accessed 2021 May 10] http://www.fivasim.com/androsensor.html .

Asim F. 2015. AndroSensor (version 2021.04.21) - Android Apps on Google Play. [accessed 2021 May 10] https://play.google.com/store/apps/details?id=com.fivasim.androsensor&hl=en.

Aumond P, Lavandier C, Ribeiro C, Boix EG, Kambona K, D'Hondt E, Delaitre P. 2017. A study of the accuracy of mobile technology for measuring urban noise pollution in large scale participatory sensing campaigns. Appl Acoust. 117:219–226. doi:10.1016/j.apacoust.2016.07.011

Babisch W, Fromme H, Beyer A, Ising H. 2001. Increased catecholamine levels in urine in subjects exposed to road traffic noise: the role of stress hormones in noise research. Environ Int. 26:475–481. doi:10.1016/S0160-4120(01)00030-7

Bai H, Wang J, Zeng AZ. 2018. Exploring Chinese consumers' attitude and behavior toward smartphone recycling. J Clean Prod. 188:227–236. doi:10.1016/j.jclepro.2018.03.253

Basner M, Samel A, Elmenhorst EM, Maab H, Müller U, Quehl J, Vejvoda M. 2011. Single and combined effects of air, road and rail traffic noise on sleep. Sleep. 34:11–23. doi:10.1093/sleep/34.1.11

Bayindir N, Paisley EW. 2018. Device: globalWebIndex's flagship report on device ownership & usage. London (UK): Trendstream Limited. Report No: H1 2018. [accessed 2021 Jen 21]. https://cdn2.hubspot.net/hubfs/304927/Downloads/Device-GlobalWebIndexSummaryReport-H12018.pdf?t=1526652356516.

Berg S. 2001. Impact of reduced reverberation time on sound-induced arousals during sleep. Sleep. 24:289–292. doi:10.1093/sleep/24.3.289

Blask DE, Brainard GC, Dauchy RT, Hanifin JP, Davidson LK, Krause JA, Sauer LA, Rivera-Bermudez MA, Dubocovich ML, Jasser SA, et al. 2005. Melatonin-depleted blood from premenopausal women exposed to light at night stimulates growth of human breast cancer xenografts in nude rats. Cancer Res. 65:11174–11184. doi:10.1158/0008-5472.CAN-05-1945

Bolin K, Bluhm G, Eriksson G, Nilsson ME. 2011. Infrasound and low frequency noise from wind turbines: exposure and health effects. Environ Res Lett. 6:035103. doi:10.1088/1748-9326/6/3/035103

Boycracked. 2016. Samsung Galaxy S7 - Full phone specifications. [accessed 2021 May 4] http://www.gsmarena.com/samsung_galaxy_s7_edge-7945.php.

Buxton OM, Ellenbogen JM, Wang W, Carballeira A, O'Connor S, Cooper D, Gordhandas AJ, McKinney SM, Solet JM. 2011. Sleep disruption due to hospital noises. Proc Inst Acoust. 33(2):618–626. doi:10.7326/0003-4819-156-12-201208070-00472

Carter NL. 1996. Transportation noise, sleep, and possible after-effects. Environ Int. 22:105–116. doi:10.1016/0160-4120(95)00108-5

Carter NL, Ingham P, Tran K, Hunyor SN. 1994. A field study of the effects of traffic noise on heart rate and cardiac arrhythmia during sleep. J Sound Vib. 169:211–227. doi:10.1006/jsvi.1994.1014

Chellappa SL, Steiner R, Oelhafen P, Lang D, Götz T, Krebs J, Cajochen C. 2013. Acute exposure to evening blue-enriched light impacts on human sleep. J Sleep Res. 22:573–580. doi:10.1111/jsr.12050

Cho JR, Joo EY, Koo DL, Hong SB. 2013. Let there be no light: the effect of bedside light on sleep quality and background electroencephalographic rhythms. Sleep Med. 14:1422–1425. doi:10.1016/j.sleep.2013.09.007

Data G. 2021 April 25. Residents in israel by communities and age groups. Data Gov (IL). [[accessed 2021]. https://data.gov.il/dataset/residents_in_israel_by_communities_and_age_groups/resource/64edd0ee-3d5d-43ce-8562-c336c24dbc1.

Dijk DJ, Archer SN. 2009. Light, sleep, and circadian rhythms: together again. PLoS Biol. 7:1–4. doi:10.1371/journal.pbio.1000145

DrMeter. 2019. Operation manual DIGITAL LUX METER 1330B. [accessed 2021 April 25]. https://drmeter.com/products/lx1330b-digital-illuminance-light-meter?_pos=1&_sid=761370e96&_ss=r.

Dutta S. 2019. Point of care sensing and biosensing using ambient light sensor of smartphone: critical review. TrAC - Trends Anal Chem. 110:393–400. doi:10.1016/j.trac.2018.11.014

Eberhardt JL, Strâle LO, Berlin MH. 1987. The influence of continuous and intermittent traffic noise on sleep. J Sound Vib. 116:445–464. doi:10.1016/S0022-460X(87)81376-7

Falchi F, Cinzano P, Elvidge CD, Keith DM, Haim A. 2011. Limiting the impact of light pollution on human health, environment and stellar visibility. J Environ Manage. 92:2714–2722. doi:10.1016/j.jenvman.2011.06.029

Falchi F, Furgoni R, Gallaway TA, Rybnikova NA, Portnov BA, Baugh K, Cinzano P, Elvidge CD. 2019. Light pollution in USA and Europe: the good, the bad and the ugly. Environ Manage. 248:109227. doi:10.1016/j.jenvman.2019.06.128

Fields JM, Walker JG. 1982. Comparing the relationships between noise level and annoyance in different surveys: a railway noise vs. aircraft and road traffic comparison. J Sound Vib. 81:51–80. doi:10.1016/0022-460X(82)90177-8

Freedman NS, Gazendam J, Levan L, Pack AI, Schwab RJ. 2001. Abnormal sleep/wake cycles and the effect of environmental noise on sleep disruption in the intensive care unit. Am J Respir Crit Care Med. 163:451–457. doi:10.1164/ajrccm.163.2.9912128

Gabinet NM, Portnov BA. 2021. Assessing the impacts of ALAN and noise proxies on sleep duration and quality: evidence from a nation-wide survey in Israel. Chronobiol Int. 00:1–21. doi:10.1080/07420528.2021.1886111

Garcia-Saenz A, De Miguel AS, Espinosa A, Valentin A, Aragonés N, Llorca J, Amiano P, Sánchez VM, Guevara M, Capelo R, et al. 2018. Evaluating the association between artificial light-at-night exposure and breast and prostate cancer risk in Spain (Mcc-spain study). Environ Health Perspect. 126:1–11. doi:10.1289/EHP1837

Garg S, Lim KM, Lee HP. 2019. An averaging method for accurately calibrating smartphone microphones for environmental noise measurement. Appl Acoust. 143:222–228. doi:10.1016/j.apacoust.2018.08.013

Gaston KJ, Bennie J, Davies TW, Hopkins J. 2013. The ecological impacts of nighttime light pollution: a mechanistic appraisal. Biol Rev. 88:912–927. doi:10.1111/brv.12036

Girschik J, Fritschi L, Heyworth J, Waters F. 2012. Validation of self-reported sleep against actigraphy. J Epidemiol. 22:462–468. doi:10.2188/jea.JE20120012

GlobalStats, 2021. Mobile vendor market share worldwide | StatCounter Global Stats_israel. [accessed 2021 April 27] https://gs.statcounter.com/vendor-market-share/mobile/israel.

Google. n.d.a Khalet al-Ghzal st'; Tamra - Google My Maps. [accessed 2021 May 4] https://www.google.com/maps/d/u/0/edit?hl=en&hl=en&mid=171eZMsdxanC8vWIGS8iAls77pgnc7Og5&ll=32.8586650125447%2C35.18942037492982&z=16.

Google. n.d.b Yitzhak Sadeh st'; Nahariya - Google My Maps. [accessed 2021 May 4] https://www.google.es/maps/d/u/0/edit?mid=1tF9sZLeR7Wxoa8ep_975rZPpmqFKigOQ&ll=38.91804996565544%2C-6.3466163601299215&z=15.

Green A, Cohen-Zion M, Haim A, Dagan Y. 2017. Evening light exposure to computer screens disrupts human sleep, biological rhythms, and attention abilities. Chronobiol Int. 347:855–865. https://doi/10.1080/07420528.2017.1324878 .

Griefahn B, Bröde P, Marks A, Basner M. 2008. Autonomic arousals related to traffic noise during sleep. Sleep. 31:569–577. doi:10.1093/sleep/31.4.569

Grossi M. 2019. A sensor-centric survey on the development of smartphone measurement and sensing systems. Meas J Int Meas Confed. 135:572–592. doi:10.1016/j.measurement.2018.12.014

GSMArena team. 2017. Samsung Galaxy A520F - Full phone specifications. [accessed 2021 April 18] https://www.gsmarena.com/samsung_galaxy_a5_(2017)-8494.php.

GSMArena team. 2020. Samsung Galaxy S20FE5G - Full phone specifications. [accessed 2021 April 13] http://www.gsmarena.com/samsung_galaxy_ace_s5830-3724.php.

Guerrini BCJ, Majumder MA, Lewellyn MJ, Mcguire AL. 2018. Citizen science, public policy. Science. 361 (80):134–136. doi:10.1126/science.aar8379

Gutierrez-Martinez JM, Castillo-Martinez A, Medina-Merodio JA, Aguado-Delgado J, Martinez-Herraiz JJ. 2017. Smartphones as a light measurement tool: case of study. Appl Sci. 7:1–18. doi:10.3390/app7060616

Haim A, Portnov BA. 2013. Light pollution as a new risk factor for human breast and prostate cancers, light pollution as a new risk factor for human breast and prostate cancers. Haifa (IL): Dordrecht Springer. doi:10.1007/978-94-007-6220-6

Hosker BS. 2018. Demonstrating principles of spectrophotometry by constructing a simple, low-cost, functional spectrophotometer utilizing the light sensor on a smartphone. J Chem Educ. 95:178–181. doi:10.1021/acs.jchemed.7b00548

Hurley S, Goldberg D, Nelson D, Hertz A, Horn-Ross PL, Bernstein L, Reynolds P. 2014. Light at night and breast cancer risk among california teachers. Epidemiology. 25:697–706. doi:10.1097/EDE.0000000000000137

Irwin A. 2001. Constructing the scientific citizen: science and democracy in the biosciences. Public Understand Sci. 10:1–18. doi:10.3109/A036852

Ising H, Braun C. 2000. Acute and chronic endocrine effects of noise. Rev Res Conduct Inst Water Soil Air Hyg. 2:7–24.

Jakovljević B, Belojević G, Paunović K, Stojanov V. 2006. Road traffic noise and sleep disturbances in an urban population: cross-sectional study. Croat Med J. 47:125–133.

Kardous CA, Shaw PB. 2014. Evaluation of smartphone sound measurement applications. J Acoust Soc Am. 135:EL186–EL192. doi:10.1121/1.4865269

Kardous CA, Shaw PB. 2016. Evaluation of smartphone sound measurement applications (apps) using external microphones—A follow-up study. J Acoust Soc Am. 140:EL327–EL333. doi:10.1121/1.4964639

Kim TH, Ramos C, Mohammed S. 2017. Smart City and IoT. Futur Gener Comput Syst. 76:159–162. doi:10.1016/j.future.2017.03.034

Kloog I, Haim A, Stevens RG, Barchana M, Portnov BA. 2008. Light at night co-distributes with incident breast but not lung cancer in the female population of Israel. Chronobiol Int. 25:65–81. doi:10.1080/07420520801921572

Kloog I, Haim A, Stevens RG, Portnov BA. 2009. Global co-distribution of light at night (LAN) and cancers of prostate, colon, and lung in men. Chronobiol Int. 26:108–125. doi:10.1080/07420520802694020

Kloog I, Portnov BA, Rennert HS, Haim A. 2011. Does the modern urbanized sleeping habitat pose a breast cancer risk? Chronobiol Int. 28:76–80. doi:10.3109/07420528.2010.531490

Kloog I, Stevens RG, Haim A, Portnov BA. 2010. Nighttime light level co-distributes with breast cancer incidence worldwide. Cancer Causes Control. 21:2059–2068. doi:10.1007/s10552-010-9624-4

Lesher AP, Gavrilova Y, Ruggiero KJ, Evans HL. 2021. Surgery and the smartphone: can technology improve equitable access to surgical care? J Surg Res. 263:1–4. doi:10.1016/j.jss.2020.12.066

Lewis RC, Gershon RRM, Neitzel RL. 2013. Estimation of permanent noise-induced hearing loss in an urban setting. Environ Sci Technol. 47:6393–6399. doi:10.1021/es305161z

Lim HM, Kang WY, Park WJ, Jang KH, Ann JS, Moon JD. 2017. Insomnia and hearing impairment among occupational noise exposed male workers. Ann Occup Environ Med. 29:1–8. doi:10.1186/s40557-017-0195-7

Machado DA, De ARC, Esteves D, Da AA, Branca PMA, De S. 2017. Accuracy of a smartphone to test laryngoscope's light and an audit to our laryngoscopes using an ISO standard. Brazilian J Anesthesiol (English Version). 180–183. doi:10.1016/j.bjane.2016.07.007

Majumder S, Deen MJ. 2019. Smartphone sensors for health monitoring and diagnosis. Sensors (Switzerland). 19:1–45. doi:10.3390/s19092164

Mallinson K. 2015. Smartphone revolution: technology patenting and licensing fosters innovation, market entry, and exceptional growth. IEEE Consum Electron Mag. 4:60–66. doi:10.1109/MCE.2015.2392954

Martin JS, Hébert M, Ledoux E, Gaudreault M, Laberge L. 2012. Relationship of chronotype to sleep, light exposure, and work-related fatigue in student workers. Chronobiol Int. 29:295–304. doi:10.3109/07420528.2011.653656

Maschke C, Harder J, Ising H, Hecht K, Thierfelder W. 2002. Stress hormone changes in persons exposed to simulated night noise. Noise Heal. 5:35–45.

Montoya FG, Peña-García A, Juaidi A, Manzano-Agugliaro F. 2017. Indoor lighting techniques: an overview of evolution and new trends for energy saving. Energy Build. 140:50–60. doi:10.1016/j.enbuild.2017.01.028

Murphy E, King EA. 2016. Testing the accuracy of smartphones and sound level meter applications for measuring environmental noise. Appl Acoust. 106:16–22. doi:10.1016/j.apacoust.2015.12.012

Nast DR, Speer WS, Le Prell CG. 2014. Sound level measurements using smartphone "apps": useful or inaccurate? Noise Heal. 16:251–256. doi:10.4103/1463-1741.140495

Oaktree Products, 2013. Digital sound level meter operation manual SL-814 [accessed 2021 April 25] https://www.oaktreeproducts.com/img/product/description/SL-814UserManual.pdf.

Odenwald S. 2020. Smartphone sensors for citizen science applications: light and sound. Citiz Sci Theory Pract. 5:1–16. doi:10.5334/cstp.254

Öhrström E. 1991. Psycho-social effects of traffic noise exposure. J Sound Vib. 151:513–517. doi:10.1016/0022-460X(91)90551-T

Öhrström E, Björkman M, Rylander R. 1980. Lab annoyance and different traffic noise sources. J Sound Vib. 70:333–341. doi:10.1016/0022-460X(80)90303-X

Ohshima H. 2015. Mobile display technologies: past, present and future. 2014 IEEE Asian Solid-State Circuits Conference, A-SSCC - Proceedings of Technical Papers. pp.1–4. Kaohsiung, Taiwan (TW). doi:10.1109/ASSCC.2014.7008845

Okada A, Inaba R. 1990. Comparative study of the effects of infrasound and low-frequency sound with those of audible sound on sleep. Environ Int. 16:483–490. doi:10.1016/0160-4120(90)90017-Z

Open Source Physics Singapore. 2019. Light analyzer (version 0.0.19)- Apps on Google Play. [accessed 2021 May 10] https://play.google.com/store/apps/details?id=com.ionicframework.lightanalyzer.

Passchier-Vermeer W. 2003. Night-time noise events and awakening, Delft: TNO Inro. Delft, Netherlands (NL).

Petrolo R, Loscri V, Mitton N. 2014. Towards a cloud of things smart city. New-York (NY), USA: IEEE COMSOC MMTC E-Letter.

Pew Research Center, 2019a. About one-in-five Americans use a smart watch or fitness tracker by Emily A. Vogels. [accessed 2020 Jen 26] https://www.pewresearch.org/fact-tank/2020/01/09/about-one-in-five-americans-use-a-smart-watch-or-fitness-tracker/.

Pew Research Center, 2019b. Smartphone ownership is growing rapidly around the world, but not always equally BY LAURA SILVER. [accessed 2020 Jen 26]. https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally.

Portaluppi F, Smolensky MH, Touitou Y. 2010. Ethics and methods for biological rhythm research on animals and human beings. Chronobiol Int. 27(9–10):1911–1929. doi:10.3109/07420528.2010.516381

Pueh H, Kian L, Lim M, Garg S. 2018. A case study of recording soundwalk of miyajima and itsukushima shrine using smartphone. Acoust Aust. 46:349–361. doi:10.1007/s40857-018-0145-8

Reinke C. 2018. Spectroid (version 1.1.1) - Apps on Google Play. [accessed 2021 May 10] https://play.google.com/store/apps/details?id=com.mazinaltokhais.trees.

Roberts B, Kardous C, Neitzel R. 2016. Improving the accuracy of smart devices to measure noise exposure. J Occup Environ Hyg. 13:840–846. doi:10.1080/15459624.2016.1183014

Rybnikova NA, Haim A, Portnov BA. 2016. Does artificial light-at-night exposure contribute to the worldwide obesity pandemic? Int J Obes. 40:815–823. doi:10.1038/ijo.2015.255

Salinas I, Giménez MH, Monsoriu JA, Castro-Palacio JC. 2018. Characterization of linear light sources with the smartphone's ambient light sensor. Phys Teach. 56:562–563. doi:10.1119/1.5064575

Sans JA, Gea-Pinal J, Gimenez MH, Esteve AR, Solbes J, Monsoriu JA. 2017. Determining the efficiency of optical sources using a smartphone's ambient light sensor. Eur J Phys. 38(2):025301. doi:10.1088/1361-6404/aa51a9

Sans JA, Manjón FJ, Pereira ALJ, Gomez-Tejedor JA, Monsoriu JA. 2013. Oscillations studied with the smartphone ambient light sensor. Eur J Phys. 34:1349–1354. doi:10.1088/0143-0807/34/6/1349

Serpanos YC, Renne B, Schoepflin JR, Davis D. 2018. The accuracy of smartphone sound level meter applications with and without calibration. Am J Speech-Lang Pathol. 27:1319–1328. doi:10.1044/2018_AJSLP-17-0171

Slabbekoorn H. 2019. Noise pollution. Curr Biol. 29(19):R957–R960. doi:10.1016/j.cub.2019.07.018

Smith MG, Croy I, Ögren M, Persson Waye K. 2013. On the influence of freight trains on humans: a lab investigation of the impact of nocturnal low frequency vibration and noise on sleep and heart rate. PLoS One. 8:1–9. doi:10.1371/journal.pone.0055829

Smolensky MH, Sackett-Lundeen LL, Portaluppi F. 2015. Nocturnal light pollution and underexposure to daytime sunlight: complementary mechanisms of circadian disruption and related diseases. Chronobiol Int. 32:1029–1048. doi:10.3109/07420528.2015.1072002

Stanchina ML, Abu-Hijleh M, Chaudhry BK, Carlisle CC, Millman RP. 2005. The influence of white noise on sleep in subjects exposed to ICU noise. Sleep Med. 6:423–428. doi:10.1016/j.sleep.2004.12.004

Su K, Li J, Fu H. 2011. Smart city and the applications. 2011 International Conference on Electronics, Communications and Control, ICECC 2011 - Proceedings. IEEE, pp. 1028–1031. Wuhan, China (CH). doi:10.1109/ICECC.2011.6066743

Svechkina A, Portnov BA, Trop T. 2020. The impact of artificial light at night on human and ecosystem health: a systematic literature review. Landsc Ecol. 35:1725–1742. doi:10.1007/s10980-020-01053-1

Taylor SM. 1982. A comparison reactions of models to predict annoyance. J Sound Vib. 81:123–138. doi:10.1016/0022-460X(82)90181-X

Topf M. 1992. Effects of personal control over hospital noise on sleep. Res Nurs Health. 15:19–28. doi:10.1002/nur.4770150105

Vallet M, Gagneux JM, Blanchet V, Favre B, Labiale G. 1983. Long term sleep disturbance due to traffic noise. J Sound Vib. 90:173–191. doi:10.1016/0022-460X(83)90527-8

Van Kamp I, Breugelmans O, Poll R, Van, Baliatsas C. 2017. Burden of disease from exposure to low frequency noise : a Dutch inventory. In: 12th Int Comm Biol Eff Noise Congr Noise as a Public Heal Probl. paper 3691. Zurich, CH: ICBN.

Van Kamp I, Van Den Berg F. 2018. Health effects related to wind turbine sound, including low-frequency sound and infrasound. Acoust Aust. 46:31–57. doi:10.1007/s40857-017-0115-6

Van Kempen E, Van Kamp I, Fischer P, Davies H, Houthuijs D, Stellato R, Clark C, Stansfeld S. 2006. Noise exposure and children's blood pressure and heart rate: the RANCH project. Occup Environ Med. 63:632–639. doi:10.1136/oem.2006.026831

Ventura R, Mallet V, Issarny V, Raverdy P-G, Rebhi F. 2017. Evaluation and calibration of mobile phones for noise monitoring application. J Acoust Soc Am. 142:3084–3093. doi:10.1121/1.5009448

Vieyra C. 2018. Vieyra Software. [accessed 2021 May 10] https://www.vieyrasoftware.net

Vieyra Software. 2021. Physics toolbox sensor suite (version 2021.04.21) - Apps on Google Play. [accessed 2021 May 10] https://play.google.com/store/apps/details?id=com.chrystianvieyra.physicstoolboxsuite&hl=en

Wahnschaffe A, Haedel S, Rodenbeck A, Stoll C, Rudolph H, Kozakov R, Schoepp H, Kunz D. 2013. Out of the lab and into the bathroom: evening short-term exposure to conventional light suppresses melatonin and increases alertness perception. Int J Mol Sci. 14:2573–2589. doi:10.3390/ijms14022573

Wakefield J. 2008. Ecologic studies revisited. Annu Rev Public Health. 29:75–90. doi:10.1146/annurev.publhealth.29.020907.090821

Waye KP, Clow A, Edwards S, Hucklebridge F, Rylander R. 2003. Effects of nighttime low frequency noise on the cortisol response to awakening and subjective sleep quality. Life Sci. 72:863–875. doi:10.1016/S0024-3205(02)02336-6

WBPhoto. 2021. Light meter (version 1-2021-05-02T22:12Z) - Apps on Google Play. [accessed 2021 May 12] https://play.google.com/store/apps/details?id=com.bti.lightMeter&hl=en&gl=US

Wilkinson RT. 1963. Interaction of noise with knowledge of results and sleep deprivation. J Exp Psychol. 66:332–337. doi:10.1037/h0044161

Williams W, Zhou D, Stewart G, Knott P. 2017. Facilitating occupational noise management : the use of a smartphone app as a noise exposure, risk management tool. Heal Saf Res Pract. 9:3–9.

Yürür Ö, Liu CH, Sheng Z, Leung VCM, Moreno W, Leung KK. 2016. Context-awareness for mobile sensing : a survey and future directions. IEEE Commun Surv Tutorials. 18:68–93. doi:10.1109/COMST.2014.2381246

Zamora W, Calafate CT, Cano JC, Manzoni P. 2017. Accurate ambient noise assessment using smartphones. Sensors (SE). 17:1–18. doi:10.3390/s17040917

Zeitzer JM, Dijk DJ, Kronauer RE, Brown EN, Czeisler CA. 2000. Sensitivity of the human circadian pacemaker to nocturnal light: melatonin phase resetting and suppression. J Physiol. 526:695–702. doi:10.1111/j.1469-7793.2000.00695.x

Zeitzer JM, Khalsa SBS, Boivin DB, Duffy JF, Shanahan TL, Kronauer RE, Czeisler CA. 2005. Temporal dynamics of late-night photic stimulation of the human circadian timing system. Am J Physiol - Regul Integr Comp Physiol. 289:R839–R844. doi:10.1152/ajpregu.00232.2005

Zhang N, Cao B, Zhu Y. 2018. Indoor environment and sleep quality: a research based on online survey and field study. Build Environ. 137:198–207. doi:10.1016/j.buildenv.2018.04.007

Zubidat AE, Haim A. 2017. Artificial light-at-night-a novel lifestyle risk factor for metabolic disorder and cancer morbidity. J Basic Clin Physiol Pharmacol. 28:295–313. doi:10.1515/jbcpp-2016-0116