The everyday acoustic environment and its association with human heart rate: evidence from real-world data logging with hearing aids and wearables

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Abstract

We investigate the longitudinal association between multidimensional characteristics of everyday ambient sound and continuous mean heart rate. We used in-market data from hearing aid users who logged ambient acoustics via smartphone-connected hearing aids and continuous heart rate from their own wearables.

We find that ambient acoustic characteristics explain approximately 4% of the fluctuation in mean heart rate throughout the day. Specifically, increases in ambient sound pressure intensity are significantly related to increases in mean heart rates, corroborating prior laboratory and short-term real-world data. In addition, however, and not previously recognized, increases in the ambient sound quality - that is, the difference between sound signal and noise - are associated with decreases in mean heart rates.

Our findings document a mixed influence of everyday sounds on cardiovascular stress, and that the relationship is more complex than is seen from examination of sound intensity alone. Thus, our findings highlight the relevance of ambient environmental sound in models of human ecophysiology.

Keywords: real-world heart rates; data-logging; everyday sounds; linear mixed-effects models; hearing loss; hearing aids

Introduction

Humans constantly face a multifaceted soundscape. Some content is by choice (e.g. listening to music), while other is not (e.g. traffic noise), but despite environmental sounds being an

integral part of everyday human life, there is very little knowledge about how acoustic aspects of the soundscape encountered in everyday life, beyond that of intensity e.g. Flamme (1), affect the human body. There is, however, increasing recognition that sounds classified as ‘noise’ have harmful effects on the human auditory (2,3) system despite being at intensity levels below those known to cause physical damage, and on the cardiovascular system (4,5). A recent report from the WHO summarized the biological mechanism of cardiovascular reactions to noise (6). In brief, it suggested that auditory noise causes both a direct (i.e. through subcortical connections of the brain) and/or indirect (involving projections from the auditory thalamus to the auditory cortex) stress reaction by disrupting the autonomic nervous system (ANS) balance due to elevated activity in the sympathetic nervous system branch and reduced activity in the parasympathetic nervous system branch (6–10), both of which control everyday fluctuations in HR. Elevation in sympathetic control leads to slow (~5 sec delay) increases in HR (11), while elevated parasympathetic control leads to fast (within milliseconds) decreases in HR (12,13). In the case of noise exposure, elevation of the sympathetic control can have acute effects that lead to momentarily elevated heart rate (HR) or blood pressure (14), or cause long-term damage, such as elevating the risk for heart disease due to sustained periods of hypertension (15). What is more, effects of noise are not always perceivable as illustrated in a study (16) in which clerical workers were exposed to simulated open-office noise. Compared to a control group they showed increased levels of adrenaline, indicative of elevated sympathetic levels, but did not report higher stress than the control group. Thus, to understand the impact of the everyday acoustic environment on the human body, objective measures of cardiovascular stress are crucial.

In a recent laboratory study a causal link between immediate noise exposure and acute cardiovascular system reactions was documented (17). They found that relative to the presence of no noise, noise segments presented at 40 dBA and 15 dBA led to a decrease in HR, while those

presented at levels of 65 and 90 dBA led to significant increases in HR. These changes were seen within 2 – 5 seconds post exposure. This timing is in line with the dynamic response of sympathetic ANS modulation of HR (12), rather than the faster acting parasympathetic control (11), suggesting that, indeed, changes in the intensity of auditory noise induce a “fight and flight” stress response in the sympathetic nervous system branch (5). Pairwise comparisons of the changes revealed significant differences in HRs between all comparison levels except for between 65 dBA and 90 dBA, suggesting a possible ceiling effect. The authors interpreted the 2% reduction in mean HR from baseline for the 15 dBA signal to be due to a fast-acting orienting response caused by the sound onset at low intensities (18). Nevertheless, beside documenting a causal link between noise exposure and HRs, their finding suggests that noise can have diverse effects on the ANS depending on its intensity. Along similar lines, Sim C. S., et al., (2015) reported that type of noise (e.g. traffic noise, background noise, speech noise) when presented at equal intensity differentially impacts heart rate variability (HRV). They argued that, besides activating a sympathetic stress reaction, noise consisting of speech also activates the parasympathetic branch leading to a more stable balance of the ANS typically represented by an increased HRV (19) and decreased HR (13).

Diverse ANS reactions to sound have also been linked to psychological evaluation and elements of active listening. Umemura M. & Honda K. (20) found that listening to classical music suppresses sympathetic nervous activity compared to rock music or noise, and that the degree of suppression (measured by Mayer Wave related Sinus Arrhythmia and respiratory sinus arrhythmia) positively correlated with subjective reports of comfort (20). On top of this, individual differences in HR responses to unpleasant noise (high speed dental engine) have been explained by individuals' familiarity and experience with the acoustic stimuli (21), indicating adaptation to commonly occurring noise sources in daily life. Regarding active listening, elevated stress levels are typically associated with listening in adverse conditions such as noise, which degrade speech recognition and

facilitate recruitment of executive cognitive resources (22). This was illustrated by Holube et al. (23), who found stress as measured with electrodermal activity correlated significantly with subjective ratings of listening effort and reported stress for listening to speech at different signal-to-noise ratios at a constant sound intensity (55 dB), indicating that stress was induced by the effort of listening. In addition to this, the reward or success importance of a given listening task has been found to modulate cardiovascular activity by sympathetic arousal (24). These findings are in line with the Framework for Understanding Effortful Listening (FUEL), which dictates that the effort expended during active listening is modulated by task demand (i.e. listening condition) and personal motivation for engagement (25). This again highlights the need for considering sound dimensions beyond intensity when assessing the effects of the everyday acoustic environment on the cardiovascular system.

Measurements of the association between human ANS balance and noise intensity have typically been performed under highly controlled conditions (i.e. in the laboratory). This eliminates the potential impact of daily life contexts, which, as pointed out above, are expected to play a significant role in ANS reactions. For example, individual sensitivity towards noise might fluctuate with time-of-day, location (e.g. home versus at work), or personal motivation, this limiting the generalizability of effects measured in the laboratory (25,26). Indeed, in a recent real-world study, it found that, over a 7-day period, increases in sound intensity were associated with a concomitant increase in HR and HRV parameters, but a delayed decrease in the overall HRV (27) reflecting withdrawal of parasympathetic and elevation of sympathetic control (19), and confirming the role of real-world noise intensity in disrupting ANS stability. In addition, they found that the strength of the association between sound intensity and change in HR was significantly moderated by place/mobility contexts, and not other parameters, which, as already noted, must be examined to understand how everyday sound immersion objectively affects the human cardiovascular system

(27,28). This notion has long been acknowledged in city planning (29,30) but has not yet been applied in the study of human stress reactions to everyday sound immersion.

In this paper, we use real-world data to investigate how everyday ANS dynamics (quantified by changes in mean HR) are associated with multidimensional characteristics of the sound environment. First, we describe the characteristics of the typical acoustic environments encountered by a sample of hearing-aid users, and second, we model how characteristics of the sound environment are associated with changes in HR throughout the day. Thus, we expand upon the current scientific evidence of how noise affects cardiovascular stress by including dimensions of the acoustic environment related to real-world listening experiences obtained from the participants' own hearing aids and wearables during daily life.

The sound environment is described using four parameters: sound pressure level (SPL), sound modulation level (SML), signal-to-noise ratio (SNR), and soundscape class, representing distinct characteristics of the momentary sound immersion. SPLs represent sound intensity and are the most commonly used indicator of the sound wave strength. SPL correlates well with human perception of loudness (31). SMLs represent temporal amplitude modulation - that is, the degree by which the sound wave amplitude oscillates over short-term intervals as found for speech and music (32). Thus, SML represents the extent to which energy in the soundwave fluctuates over a short time-window. SNRs represent a spectral dimension of the sound by differentiating between the level of background noise relative to the level of the signal in decibels. A more positive value indicates less noise relative to signal. Finally, soundscapes are a qualitative dimension of the acoustic environment assumed to relate to how effortful it is to listen to speech-like sources in the presence of different levels of background noise (33,34).

Methods

Participants and Ethics

Participants were users of Oticon Opn hearing aids (Oticon A/S, Smørum, Denmark), who had signed up for the HearingFitness™ feature via the Oticon ON™ remote control app. When signing up for the HearingFitness™ program via the app, users submitted their consent agreeing to use of their anonymized data (i.e. no personal identifiers are available) for research purposes on aggregated levels (i.e. no single-case investigation are performed) and agreed that data could be stored on Oticon A/S owned secure servers. In addition, users gave specific consent permitting access to their GPS location (as a relative measure in meters between each sample) and health data from Apple Health Kit. All data collection and storage were conducted in a "privacy by design" manner in accordance with the General Data Protection Regulation (EU regulation 2016/679). No ethical approval was necessary for this study according to Danish National Scientific Ethical Committee (https://www.nvk.dk/forsker/naar-du-anmelder/hvilke-projekter-skal-jeg-anmelde).

Data sources and Apparatus

Data were obtained from the commercially available HearingFitness™ program (35), which is offered to users of Oticon A/S internet-connected hearing aids. All participants had paired their Oticon Opn™ hearing aids with the Oticon ON™ iOS smartphone app for remote control with HearingFitness™ enabled. The HearingFitness™ program activates automatic logging of sound data from the hearing aid microphones together with extraction of health data from the Apple HealthKit app associated to a user-owned wearable. No information regarding the type and model of the user-owned wearable was available, however, health data from consumer wearables represent a promising source of data for observational studies (36,37).

We extracted a convenience sample of real-world data from 98 in-market users between June and December 2019. Given the real-world nature of the data and the privacy-preserved extraction, no personal information characterizing the users (e.g. age, gender) are available. However, the users represent a random sample of typical hearing aid users, thus, we expect that 6 in 10 are male, and are aged around 74 years (38).

Acoustic variables collected

Data concerning the acoustic environment were logged by the smartphone-connected hearing aids. Data consist of three continuous acoustic variables and one discrete soundscape variable. The continuous data represent acoustic characteristics of the momentary soundwave sensed by calibrated hearing aid microphones at ear level. These variables are: SPLs, SMLs, SNRs all estimated in a broadband frequency range (0-10kHz) in decibel units (see Figure 1B). SPL is the level output estimate from a low-pass infinite impulse-response filter with a time constant of 63ms. SML is then derived as the difference between a top- and bottom tracker (peak- and valley detector) of the SPL. The bottom tracker is implemented with a slow dynamic attack time of 1s to 5s and a fast release time of 30ms and the top tracker is implemented with the reverse (see Figure 10-3 in Kates, 2008). SNR is the difference between the bottom tracker and the immediate SPL. Thus, values of SPL and SNR are dynamically changing on same time scale whereas the SML changes with a slower time constant of up to 5 seconds. The discrete soundscape variable classifies the momentary sound environment into four soundscapes by a proprietary hearing aid algorithm using SPL, SML and SNR values. The soundscapes are: “Quiet”, ”Noise”, ”Speech”, and “Speech in Noise”. Similar soundscape classification from hearing aids have been reported as a potential source for data mining (40). Figure 2 shows distributions of soundscapes against each of the three continuous acoustic data variables.

Data logging

Data of the acoustic environment were logged every 60 seconds together with timestamps indicating when the hearing aids were turned on and connected via Bluetooth to a smartphone. The 5-min running mean HR was extracted from the Apple HealthKit storage (https://developer.apple.com/documentation/healthkit) approximately every 7 minutes (observed mean = 7.6 minutes, SD = 2.8 minutes) when a wearable with a heart rate sensor was connected to the smartphone.

Data extraction and filtration

Data from 98 unique individuals were extracted. In total, 1,115,332 acoustic environment data logs and 522,715 heart rate logs were obtained, which represents approximately 9,000 hours of bilateral hearing aid use and 61,000 hours of data from wearables respectively. Only data logged between 06:00 and 24:00 were considered valid to avoid confounds from night-time logs that were likely collected when neither the hearing aids nor wearables were being worn.

Data were examined in two stages. First, in order to maximize the data available the acoustic environment were described using all observations regardless of temporal overlap with HR logs. Second, for subsequent association analyses, the data were pre-processed to ensure full overlap between acoustic variables and HR logs. Pre-processing consisted of selecting time windows of five minutes prior to each HR log and computing the arithmetic average of each acoustic variable within that window. Thus, the fully overlapping data consists of data records with the value of each acoustic data variable estimated from the same time window as the running mean HR logs. We excluded data records with HRs that were below the 5th percentile and above the 95th percentile of the group mean HR to avoid potential confounds from low incident HRs (36). Exclusion of these data ensured normality of residuals from statistical modeling but did not affect the order of regression coefficients (Table 1) or the statistical significance of the included statistical

models. Further, we only included participants for whom there were at least 50 overlapping HR and acoustic data logs. After pre-processing, our data consisted of 25193 data records from 56 users and 971 unique user days. Figure 3A shows the count of data records separated by time-of-day and weekday, and Figure 3B shows the density distributions of each variable in the data records.

The effective sampling period of data records was dependent on the proportion of time that a user simultaneously wore their hearing aid(s) and a wearable while each was connected to a smartphone. As is typical of hearing aid users, participants wore their hearing aids for different durations throughout the day. This was true both within and across participants. Thus, we estimated the effective sampling frequency (i.e. representativeness of samples across time) by computing the average amount of data records each hour between 6:00 and 24:00 per user across the period covered in the data. The grand average sampling frequency across all 971 user days and hours was 2.11 data records per hour (SD = 2.42) with a peak at 19:00 (2.21 data records per hour, SD = 1.72).

Adjusting for movement

A subset of the dataset contained GPS information associated with each HR measure. This was used to examine the possible confounding effect of movement on the relationship between HRs and sound environment data. Movement was estimated within the database and extracted for analysis. Specifically, the distance in meters between two consecutive latitude and longitude coordinates was computed using the haversine method. Using this method, for each pair of subsequent latitude (φ_1, φ_2) and longitude (λ_1, λ_2) coordinates the distance between them in meters, d, is estimated as:

$$d = 2r\arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right)}\right), \quad [1]$$

with *r* being equal to the radius of the earth. Movement in meters/sec was then computed by dividing *d* with the 1-min time-window between each observation and averaging across the 5-min time-window preceding each HR measure. To ensure that only movement due to physical activity was considered, data records with movement that exceeded cycling speed (10 meters/sec) was excluded.

Statistical analysis

Due to the unbalanced (unequal samples per user, day, hour etc.) and hierarchical multi-level nature of the data records, associations between variables were quantified using linear mixed-effect (LME) models. LME models were applied separately for predicting mean HR from either the categorical soundscape or the acoustic data (SPL, SML, and SNR). In addition, an interaction model was applied to test the hypothesis that soundscape moderates the association between acoustic data and mean HR. The random-effects structure was adjusted for individual differences in baseline HR and sensitivity towards each fixed-effect (i.e. random intercepts and slopes) and adjusted for baseline offsets in HRs due to time-of-day (in hours), and weekday nested within individuals (Barr et al., 2013). In separate models, adjustment for movement was applied by adding an additional nested random effect equal to the estimated movement (see previous section) and quantified into 10 separate bins (deciles).

The autocorrelation of residuals was addressed with a first-order autoregressive structure, which has previously been shown to improve the goodness-of-fit with similar data of mean HRs (27).

All statistical analysis and visualizations were done in R version 3.6.1. For application of mixed-effects models, the “nlme - Linear and Nonlinear Mixed Effects Models” package (version 3.1) was used (42).

To assess the degree of multicollinearity within the models, particularly with the addition of acoustic characteristics and their interaction with soundscape, the generalized variance inflation factor (GVIF) was computed using the "car" package version 3.0.8 (43). The GVIF is a generalization of the variance inflation factor (VIF) that can be applied to categorical explanatory variables (44). Values of GVIF < 4 are usually considered to be acceptable (45). Visualizations were done with "ggplot2" package (version 3.3.2).

Besides inspecting the magnitude and confidence intervals of the standardized coefficients, partial variance explained by the fixed effects, R_P^2 ,was estimated based on recommendations for multilevel hierarchical models (46). Briefly, the sum of residual sum of squares across each grouping level of the models including both fixed and random effects were compared to those from intercept-only models with identical random effects. Explained variance of the fixed effects were then computed as the proportional reduction in prediction error at the individual level (47),

$$R_P^2 = 1 - \frac{\sigma_F^2+\tau_F^2+\gamma_F^2}{\sigma_N^2+\tau_N^2+\gamma_N^2}, \qquad [2]$$

where σ_F^2 represents the level-one (subject) residual sum of squares for the full model; τ_F^2 represents the level-two (weekday) residual sum of squares for the full model; and γ_F^2 represents the level-three (time-of-day) residual sum of squares for the full model. The terms in the denominator represent residual sum of the squares for the same three levels but for the intercept-only (null) model. To estimate the explained variance of the full model including random effect terms (R_F^2) the denominator in Equation 2 was replaced with the total sum of squares from the observations (i.e. the "natural" variance).

Model diagnostics were conducted in accordance with recommendations in the literature (48), and we ensured that models adhered to assumptions of normality of residuals and homogeneity of variance among random-effect groups (see the Electronic Supplementary Material).

Results

Data validation

Before examining the association between acoustic data and HRs, descriptive analyses were conducted to assess the data validity.

The median SPL across all users was 54.42 dB (SD = 6.68 dB), which corresponds to a level just below normal conversational speech (~60 dB). The values of each acoustic characteristic varied according to the soundscape as classified by the hearing aid (see Figure 1 and 2). Specifically, as expected, “Speech” environments consisted of higher values of raw SNR and SML, while “Speech in Noise” and “Noise” had the highest SPL. This provides validity for the soundscape classification.

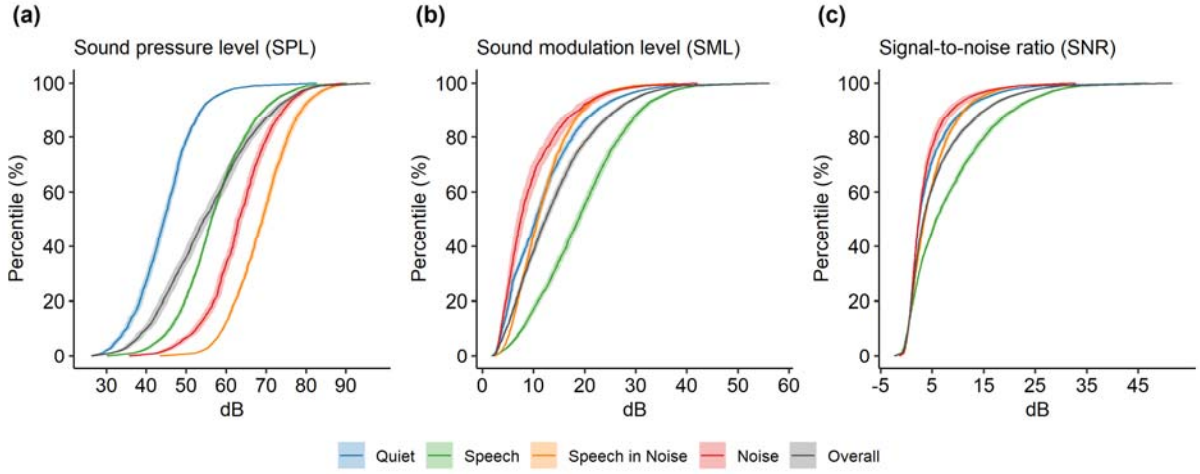


Figure 1: Cumulative distribution functions of raw acoustic data separated by soundscape. Median sound pressure level (a), sound modulation level (b), and signal-to-noise ratio (c) for each percentile across users.

We also examined the variation in sound data as a function of time of day. In Figure 2(a), each acoustic characteristic is plotted as standard scores, while Figure 2(b) shows the relative occurrence of each soundscape by time of day. As would be expected, the SPL is lowest late in the evening (22:00 and 23:00), slightly higher in the morning (6:00 to 8:00), and highest around lunchtime (12:00) and dinner time (18:00). The proportion of time the sound environment was classified as being "Quiet" was also highest in the evening (from 20:00) and early morning (6:00 to 9:00). Conversely, the proportion of time the ambient acoustic environment was classified as "Speech" was greatest early evening (16:00 to 21:00), which corresponds in time to when the SML was also greatest. Similar findings have been reported in other studies (49).

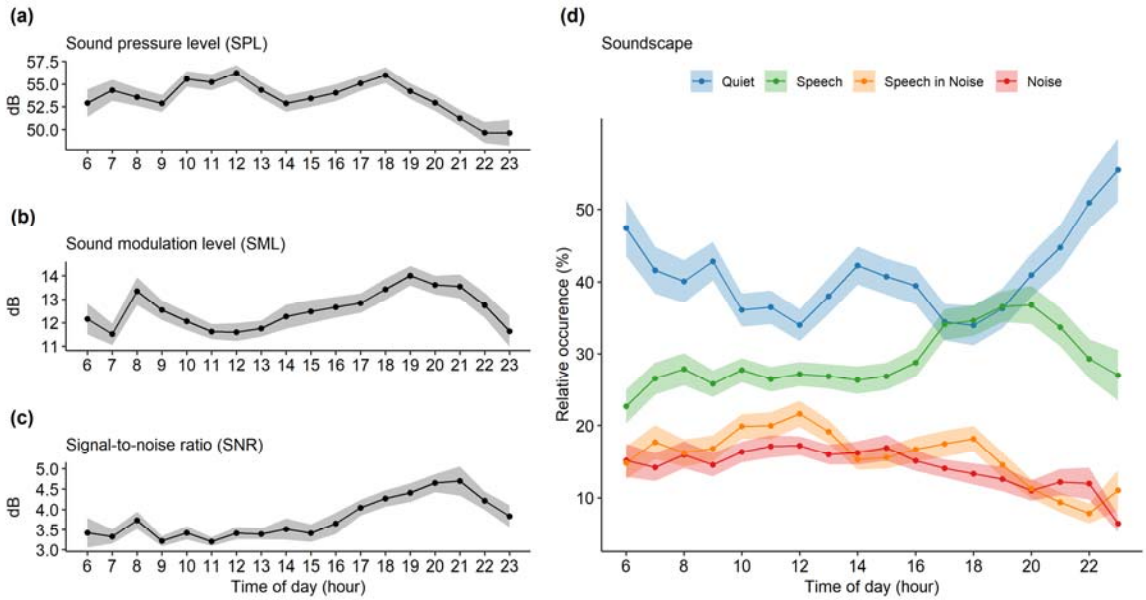


Figure 2: Everyday acoustic environment. (a)-(c) grand averages of the continuous acoustic data for each hour of the day. (d) grand averages of the most often occurring soundscape for each hour of the day. The grand averages are computed as median values across all data for each hour for each user and then across all users. Shaded area represents the standard error of the mean.

We interpret the temporally fluctuating acoustic environment characteristics as reflecting differing everyday contexts, with Figure 2(d) suggesting that for approximately 65% – 70% of the day, the acoustic environment is classified as "Quiet" or "Speech". This is similar to the findings of Humes,

L. E. et al. (49), who found that older adults with hearing aids typically spent 60% of their time in "quiet" or "speech-only" conditions, while around 10% of time is being spent in "pure noise". This, combined with the face-validity of the data, provide evidence that our acoustic data reflect real-world characteristics.

The grand mean HR was 75.60 bpm (SD = 6.89 bpm), which is lower than the normative value of 79.1 bpm (SD = 14.5 bpm) for individuals aged 18 years and older (50). Our values might differ due to the age distribution of our population combined with the fact that HR declines with age (51). Our study population consists of hearing aid users and the average age of first-time hearing aid users is around 69 years (38). When comparing our data with the mean real-world HR for people aged 71 to 80 years the values are much closer: 74.2 bpm (SD = 11.1 bpm) versus 75.60 bpm (SD = 6.89 bpm) here.

Association between sound and heart rate

The association between acoustic characteristics and mean HRs were investigated with the subset of data with overlapping acoustic and HR information

Figure 3 shows summary distributions of these data records. Figure 3(a) indicates a close to uniform sampling of observations from 10:00 to 20:00 and across weekdays except for Friday and Sunday, which exhibits approximately 500 - 1000 less records than the rest of the week. When averaged across all users, 35% (SD = 20%) of data records were registered as being a "Quiet" soundscape, 32% (SD = 18%) as a "Speech" soundscape, 18% (SD = 14%) as a "Speech in Noise" soundscape, and 15% (SD = 12%) as a "Noise" soundscape.

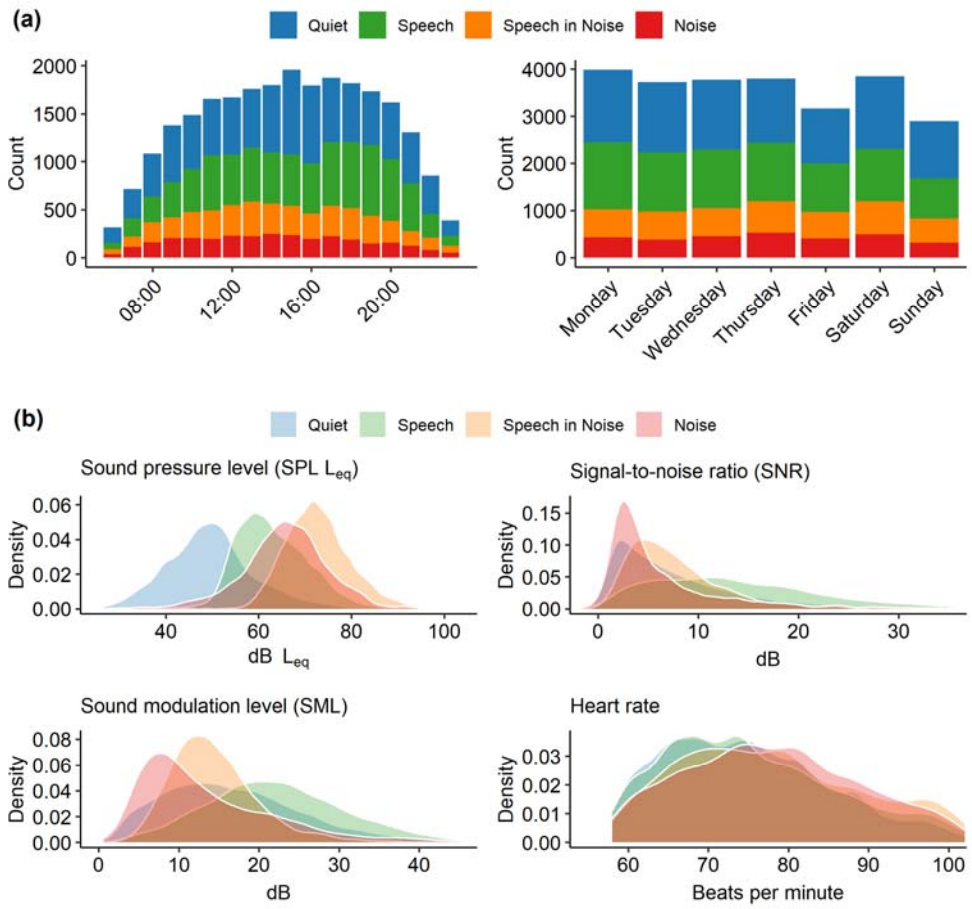


Figure 3: Overview of data for statistical modeling. (a) total counts of data records for each hour of the day (left) and weekday (right) for each soundscape class (colors). (b) density distributions for each acoustic data variable and the heart rates. Note that data records with HR below the 5th or above the 95th percentile were excluded prior to visualizing (see text for details).

Density distributions of the continuous acoustic parameters associated with each data record are shown in the first three panels of Figure 3(b). Not surprisingly, the sound intensity (SPL) was highest for "Speech in Noise" and "Noise" soundscapes with median SPL L_{eq} being 72.47 dB (SD = 3.87 dB) and 65.97 dB (SD = 7.34 dB), respectively. For comparison, the same value in "Quiet" was 48.79 dB (SD = 5.25 dB). These values correspond well with those reported by El Aarbaoui & Chaix (27) for differing contextual locations (i.e. "Public" and "Transportation" versus "Home"). Regarding SNR, as would be expected, the "Quiet" and "Noise" soundscapes exhibited lower median values (Quiet: 4.89 dB, SD = 3.86 dB, Noise = 3.81 dB, SD = 2.50 dB) compared to

"Speech" (12.50 dB, SD = 5.14 dB). These values are in line with previously reported real-world data (52,53). Lastly, median SML was highest for "Speech" and "Quiet" (Speech = 21.77 dB, SD = 6.45 dB, Quiet = 15.28 dB, SD = 5.84 dB) and lowest for "Noise" (11.57 dB, SD = 4.69 dB), indicating that, indeed, SML represents modulated sound with low levels of noise.

The last panel of Figure 3B shows the distribution of HR across all valid records Mena HR values differed by soundscape. "Quiet": 74.6 bpm (SD = 6.9 bpm); "Speech": 75.9 bpm (SD = 7.0 bpm); "Speech in Noise": 78.2 bpm (SD = 8.6 bpm); and "Noise": 77.6 bpm (SD = 6.9 bpm). A repeated measures ANOVA shows a significant main effect of soundscape ($F(1.94,103.03) = 9.39$, $p = 0.034$), with post hoc comparisons using Bonferroni correction indicating that the mean heart rate for "Quiet" was significantly lower than for "Speech" ($p = 0.017$), "Speech in Noise" ($p < 0.001$), and "Noise" ($p < 0.001$); the mean heart rate for "Speech" was significantly lower than for "Speech in Noise" ($p = 0.019$), but not for "Noise" ($p = 0.12$). HRs for "Speech in Noise" and "Noise" did not significantly differ.

Marginal mean HR at increasing levels of each acoustic characteristic are shown in Figure 4. The marginal mean HR was computed by first standardizing each participants's HR and acoustic data (centering and scaling) and then computing the pooled average HR within non-overlapping bins for deciles of SPL, SNR and SML. For example, the first bin in Figure 4 (centered at 5% on the x-axis) represents the average standardized HR for values of acoustic data falling between the 0% and 10% quantile. The standardization of acoustic characteristics was done to prevent confounds from inter-individual differences (e.g. hearing aid microphone placement and offset) in stratifying HRs.

Since high levels of SNR and SML can occur for both low and high levels of SPL (see Figure 6), we computed the marginal mean HR versus SML and SNR in two regions of SPL: SPLs below and above the overall median (i.e. L_{eq} = 60 dB SPL).

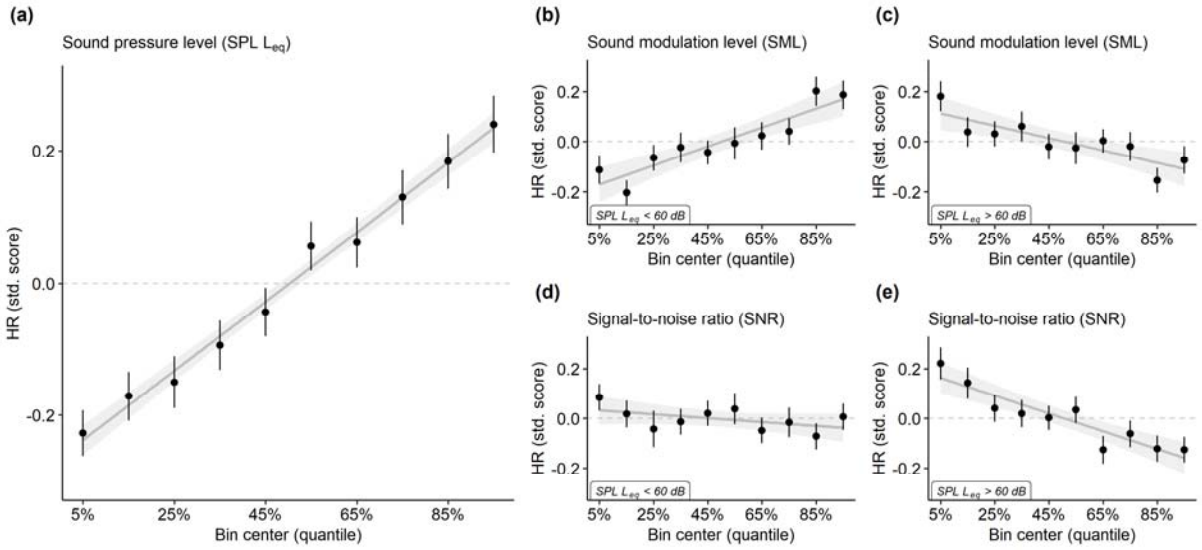


Figure 4: Marginal means of heart rates (HRs) separated by deciles (decile centers on x-axis) of the acoustic characteristics. Solid lines represent best fitting linear regression. (a) HR versus SPL L_{eq} (β = 0.05, F(1,8) = 886.70, p < 0.001, R^2 = 0.99). (b) HR versus SNR at low intensities (β = -0.01, F(1,8) = 2.30, p = 0.132, R^2 = 0.27). (c) HR versus SNR at high intensities (β = -0.04, F(1,8) = 61.86, p < 0.001, R^2 = 0.86). (d) HR versus SML at low intensities (β = 0.04, F(1,8) = 45.39.31, p < 0.001, R^2 = 0.85). D) HR versus SML at high intensities (β = -0.02, F(1,8) = 20.76, p = 0.002, R^2 = 0.72). The marginal means were computed separately for data records within each decile of the acoustic characteristics. Prior to computation of the marginal means, SPL, SNR, SML, and HR data were standardized (centered and scaled) for each participant. The threshold between low and high intensity environments is based on the pooled median observed SPL (L_{eq} = 60 dB).

The marginal means and fitted linear trends in Figure 4 indicate a strong association between acoustic characteristics and HRs. In addition, Figure 4 (b)-(e) reveals that the association between derived moments of the sound wave (i.e. SNR and SML) and mean HR is conditional on intensity. That is, a comparison of Figure 4(d) and 4(e) show that SNR is more strongly associated with HR when the SPL L_{eq} is above rather than below 60 dB (i.e. steeper slope of the regression) while

Figures 4(b) and 4(c) indicate that SML is either positively associated with HR at lower SPLs or negatively associated with HR at higher SPLs.

As stated in the introduction, everyday sounds are not only modulated by intensity but also by dynamic characteristics (i.e. modulated or not), perceptual quality (i.e. noisy or clean signals), and type (e.g. conversation, music, traffic). These distinct traits can be approximated by SPL, SML, SNR, and soundscape, respectively. However, these acoustic dimensions inherently correlate. For example, high intensity speech signals (high SPLs) also have a high SML, and if not masked by noise, a high SNR. This is evident from Figure 5, which shows the interrrelations between SPL, SML, SNR, and soundscape as 2D density distributions. The the potential confound of multicollinearity in the LME model for acoustic data was assessed by computing the generalized variance inflation factor (GVIF, see *Methods*). The GVIF was 1.05, 1.17, and 1.22 for SPL, SML, and SNR, respectively, indicating that multicollinearity was not a problem (45).

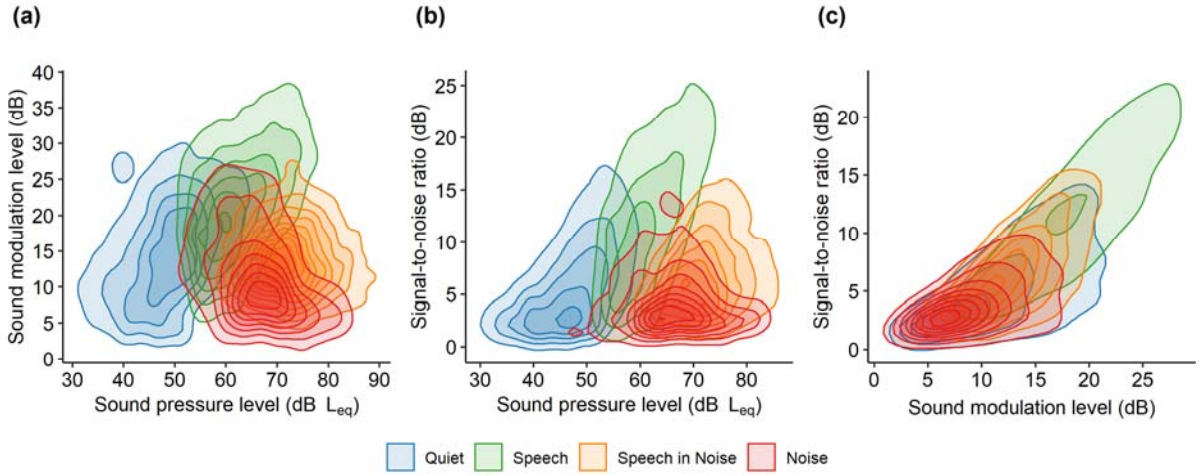


Figure 5: Relationship between each acoustic variable and the soundscape in the data records as 2D density distributions. (a) SML versus SPL. (b) SNR versus SPL. (c) SNR versus SML.

However, given the high degree of clustering of the continuous acoustic data with soundscape we included the two types of data as independent variables in separate models to predict HRs. We next

fitted the models to a subset of the observations which included GPS data investigate the influence of controlling for movement activity estimated from relative GPS coordinates (see *Methods*).

Table 1: Regression coefficients (β) and 95% confidence intervals of the change in mean heart rate (bpm) associated with a change in soundscape (Soundscape model) or a 1 SD change in either SPL, SML or SNR (Acoustic data model). Models were fitted to either all data records (observations) or to only those observations that contained movement data. In the latter case, movement was included as a (nested) random effects term.

	All obs. (n = 25193)		W. movement (n = 5613)	
	β	*95% CI*	*β*	95% CI
Soundscape model				
S vs Q	+1.07	[+0.81 to +1.33]	+1.46	[+0.91 to +2.00]
SN vs Q	+2.23	[+1.89 to +2.57]	+1.85	[+1.17 to +2.53]
N vs Q	+2.61	[+2.25 to +2.97]	+1.84	[+1.03 to +2.66]
Acoustic data model				
SPL	+1.47	[+1.29 to +1.76]	+1.39	[+0.89 to +1.90]
SML	+0.72	[+0.49 to +0.95]	+0.53	[+0.06 to +0.99]
SNR	-1.03	[-1.26 to -0.79]	-0.86	[-1.21 to -0.51]

Note: S: Speech; Q: Quiet; SN: Speech in Noise; N: Noise

Inclusion of sound data to predict heart rates significantly improved model goodness-of-fit when compared to intercept-only models with Likelihood-ratio tests (acoustic data: χ^2 (6) = 723, p < 0.001; soundscape data: χ^2 (3) = 277, p < 0.001), confirming a significant association between changes in mean HR and the acoustic environment. The estimated partial variance explained was 4.25% for the acoustic data model and 1.43% for the soundscape model (Table 2).

The acoustic data model revealed distinct associations between HR and different acoustic characteristics. Specifically, the regression coefficient for SPL is larger than for SML and SNR (non-overlapping confidence intervals), and the regression coefficient for SNR has negative

signage, whereas both SPL and SML are positively associated with HR. These effects were not caused by motion (i.e. sound and HR changing in response to latent physical activity), which is indicated by the finding that the adjusted vs. non-adjusted for movement acoustic data model had similar coefficient magnitudes and overlapping confidence intervals (Table 1), while the adjusted model explained approximately 10% additional HR variance (see Table 2). This indicates that the additional explained variance did not covary with acoustic data – that is, the movement predictor captured HR variance unrelated to variance captured by the acoustic data predictors.

The regression coefficients for the soundscape model confirmed the trend present in Figure 3(b) lower right that; HR increases as the complexity of the soundscape increases from “Quiet”, to “Speech”, to “Speech in Noise” and finally “Noise”. Thus, despite “Speech in Noise” having the highest SPL (Figure 1(a)), HRs were overall higher in soundscapes classified as noise. The movement adjusted soundscape model likewise yielded a 10%-point increase in explained variance (Table 2), however, the coefficients (Table 1) suggests that a change from “Quiet” to “Speech in Noise” and from “Quiet” to “Noise” results in approximately the same change in mean HR. In addition, these changes are lower in magnitude as was the case for the non-adjusted model. This indicates that, indeed, movement might have influenced the change in mean HR when contrasting “Speech” with more complex “Speech in Noise” and “Noise” soundscapes.

Table 2: Explained variance by fixed effects (R_P^2) and the full model including both fixed and random effects (R_F^2). Note that data in the Interaction model were collapsed across "Speech in Noise" and "Noise" soundscapes.

	R_P^2	R_F^2
All observations (n = 25715)		
Soundscape model	1.43%	56.28%
Acoustic data model	4.25%	57.22%
Interaction model	4.54%	57.30%
Observations w. movement (n = 5919)		
Soundscape model		
With movement random effect	0.61%	72.12%
Without movement random effect	0.78%	62.11%
Acoustic data model		
With movement random effect	2.52%	72.56%
Without movement random effect	2.76%	62.86%

The median movement in the time-window preceding each HR observation was 0.15 m/sec (SD = 1.55 m/sec), suggesting that most of these observations were associated with little movement although a significant linear relationship was observed between movement and mean HR (LME adjusted for participant, β = 0.39, 95% CI = [+0.22 to +0.57], t = 4.40, $p < 0.001$).

Moderating effect of soundscape

The data in Table 1 suggest that changes in mean HR throughout the day are significantly associated with changes in soundscapes, and that overall mean HRs are lower in less complex soundscapes (e.g. "Quiet" versus "Speech in Noise"). Here, we investigated the extent to which the soundscape moderated the strength of the association between HR and its acoustic characteristics. That is, were users more sensitive towards acoustic characteristics in certain

soundscapes? We would expect this to be true since differences among soundscapes proxy differences in listening conditions. For instance, it is less effortful to understand speech in a quiet environment than in a noisy one. To examine this we fitted an interaction model for data from "Quiet", "Speech" , and "Noisy" soundscapes, reflecting increasing levels of soundscape complexity. The "Noisy" consisted of data from the "Speech in Noise" and "Noise" soundscapes combined since they were highly overlapping in terms of acoustic characteristics (Figure 5) and contained the fewest observations (Figure 3).

We fitted an interaction model with each acoustic parameter being allowed to interact with soundscape while keeping the same random-effects variance structure as before. For this model, we used all observations and did not include movement as a random-effect term since the additional degrees-of-freedom would otherwise render the model un-identifiable. The interaction model produced better predictions than both the soundscape model (ΔAIC = 270.5, chi2(11) = 292.54, p < 0.001) and the acoustic data model (ΔAIC = 12.6, chi2(8) = 28.6, p < 0.001) and were able to explain slightly more of the HR variance (Table 2). Despite the potentially high covariance between soundscape and acoustic data, the largest GVIF was estimated to be 1.79 (the interaction between soundscape and SNR), which again indicates that multicollinearity was not an issue (45).

The main effects replicated the outcomes of fitting the acoustic data and soundscape models separately (see Table 1). That is, we see higher HRs for more complex soundscapes ($F(2) = 26.39$, $p < 0.001$), more intense and modulated sound environments (SPL: $F(1) = 68.48$, $p < 0.001$; SML: $F(1) = 30.04$, $p < 0.001$), and environments with more background noise (SNR: $F(1) = 15.35$, $p < 0.001$). Additionally, interactions between soundscape and SPL, SML were significant ($F(2) = 5.21$, $p = 0.006$; $F(2) = 15.64$, $p < 0.001$).

Figure 6 shows each level of the three interactions between acoustic variables and soundscape. It indicates that interactions were driven by differences in strength of association between "Quiet"/"Speech" and "Noisy" soundscapes. Thus, observed HRs were more strongly associated with sound intensities and modulation levels when the ambient acoustic environment was classified as being favourable for listening (i.e. in quiet and speech-dominated soundscapes).

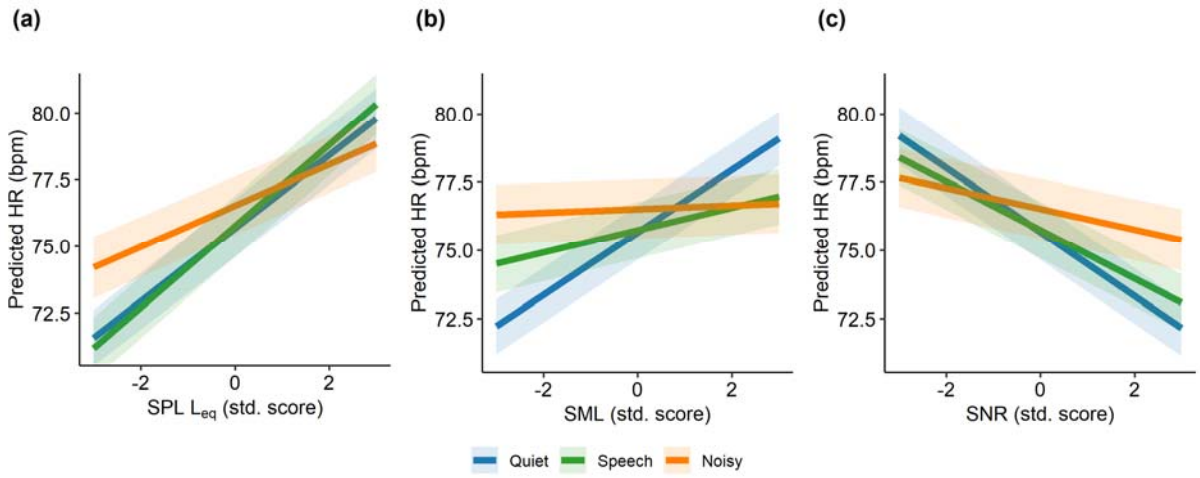


Figure 6: Predicted regression lines from the LME interaction model of the coefficients SPL (a), SNR (b), and SML (c). Shaded area represents the standard error around each prediction.

We assessed the significance of each pairwise interaction by contrasting each coefficient (i.e. slope) with the "Quiet" soundscape as baseline. For SPLs, the slope for "Noisy" soundscape was significantly lower than for "Quiet" (β = -0.60, SE = 0.23, p = 0.008) whereas the slope for "Speech" did not differ from the slope for "Quiet" (β = 0.16, SE = 0.24, p = 0.51). For SNRs, the slope for "Noisy" was significantly less steep than for "Quiet" (β = 0.79, SE = 0.24, p < 0.001). Finally, for SMLs, slopes for both "Speech" and "Noisy" were significantly lower than for "Quiet" (β = -0.74, SE = 0.18, p < 0.001; β = -1.08, SE = 0.21, p < 0.001).

Effect size considerations

The explained variance of the acoustic data model (Table 2) suggests that ambient acoustics (i.e. SPL, SML, and SNR) explain around 4% of the within-individual variation in 5-min mean HRs. In order to assess the magnitude of the regression coefficients, and to compare our findings from hearing impaired individuals with those from El Aarboui & Chaix (27) using normal hearing individuals, we re-fitted the acoustic data model after log-transforming the HRs while keeping predictors (SPL, SML, and SNR) in their original dB scale. Back-transformation of the coefficients with (exp(β)-1)*100 yields percentage change in 5-min mean HR with 1 dB change in the level of either SPL, SML or SNR. After re-fitting, the coefficients were SPL: β = 0.154, 95% CI [+0.127 to +0.181]; SML: β = 0.112, 95% CI = [+0.078 to +0.145]; and SNR: β = -0.169, 95% CI = [-0.209 to -0.130]. For comparison, El Aarboui & Chaix (27) documented a 0.141% (95% CI = [+0.135 to +0.148]) change in mean HR (5-min window preceding each HR measure) from a 1 dB(A) change in SPL.

Discussion

Using real-world data from in-market hearing aids we were able to investigate the association between exposure to everyday acoustic characteristics and short-term (i.e. within 5 minutes) changes in HR. The data reflect hearing-aid use over several weeks and as such represents the acoustic environment expected from everyday life activities (see Figure 1 and 2), with characteristics of intensity and soundscape occurrences that agree with previous research (1,49,53).

We found that characteristics of the sound environment were significantly associated with changes in heart rate. Specifically, higher SPLs and SMLs were associated with increased HRs, whereas more favourable (higher) SNRs were associated with lowered HR. These results reproduce earlier findings from other research groups (27), and expand the evidence to also include

other dimensions (i.e. SML, SNR, and soundscape) of the acoustic environment. In addition, all associations were stronger in simple listening soundscapes ("Quiet" and "Speech") compared to soundscapes classified as containing noise, while marginal means revealed that HR moderation by SMLs and SNRs were distinct, depending on sound intensity. Specifically, marginal means suggested that the negative association between SNR and mean HR was most pronounced in sound environments where the SPL L_{eq} exceeded 60 dB, whereas sound modulation was more strongly associated with increases in HR at intensity levels below 60 dB.

SPLs are directly associated with loudness perception (31) and have been found to induce activation of the sympathetic branch of the human ANS (5,17,27). Our study suggests that even everyday SPLs (i.e. levels well below those typically defined as hazardous to the auditory system) also affect heart rate. Thus, we speculate that the ANS is moderated by sound pressure - regardless of the level of sound intensity.

We also documented a positive, albeit smaller, association between HR and SML. SML reflects sound wave modulation. Highly modulated sound is typically characterized by fast oscillating SPLs, which are indicative of speech or music. We speculate that the positive association between SMLs and HRs are, to some extent, caused by task demands (54). That is, in highly modulated sound environments, listening and speech demands are increased, which leads to slightly increased sympathetic ANS activity. This speculation is corroborated by the fact that the positive association between SML and HR is stronger for low-intensity simpler acoustic environments than for louder noisy environments, i.e. Figure 4(d) and 6(c), which suggests the association is being driven by task-related activities.

We also documented a negative association between real-world HRs and SNRs. This finding corroborates laboratory research within the hearing sciences, which shows that difficult

listening conditions (e.g. characterized by low SNRs) increases the listening effort needed for speech understanding, and thus, either elevates the sympathetic stress levels or decreases the parasympathetic ANS activity seen as increased pupil dilation (55,56) or skin conductance (54) and decreased HR variability (57). This suggests that the ambient SNR, as measured by the hearing aids, could proxy as a real-life indicator of momentary and contextual listening difficulty, while associated changes in HR might indicate the level of mobilized listening effort (25).

The sound data used in this study were measured by commercial hearing aid devices. These devices are typically optimized for low power consumption, which typically would entail lower resolution and accuracy of sound estimators. Despite this, summary statistics of our data agree with other studies using devices specifically developed for research purposes (27). This highlights a potential for exploiting commercial devices, and in particular, hearing aids, for obtaining real-world evidence about human behavioural and biological reactions to environmental sound stimuli. For example, future studies using a similar setup could investigate how sensitivity towards specific acoustic characteristics differ between populations with various underlying health pathologies. Indeed, previous research has already documented the use of similar hearing aid data logging for policy-making within the hearing or public health domains (58,59).

Limitations

The users in our dataset do not represent the general population because all were hearing-aid users, thus, they have some degree of hearing loss and are likely older. Some studies suggest that the older people with hearing loss spend more time in quiet sound environments than younger and normal hearing individuals (60). Moreover, hearing loss can lead to increased sensitivity towards noisy and loud sound environments, which might have impacted the associations listed in Table 1. However, comparing the magnitude of the regression coefficient for SPL with that

of El Aarboui & Chaix (27) suggests that age and hearing abilities did not affect the associations found here.

Heart rates are sensitive to both sympathetic and parasympathetic ANS influence. However, in the current study only mean HRs are reported. This means that an in-depth investigation of the extent to which stress is caused by elevation in sympathetic activity or withdrawal of parasympathetic activity is not possible here. Future studies could consider leveraging data available from commercial wearables that measure continuous heart rate variability (HRV). This might reveal distinct contributions from the sympathetic and parasympathetic branch of the ANS (19) in response to different sound exposures, representing distinct cognitive and physiological processes. Indeed, short recordings of HRV have been shown to be stable across longitudinal studies (61).

Finally, the data assessed in the current study is considered real-world in nature, which means that there was no control over who used what devices, when, and how often. In addition, we did not have information regarding data quality from each wearable device manufacturer, and thus cannot give estimates regarding the clinical validity of the HR data. However, we do not expect data quality to have biased our findings since the validity of real-world data has been documented (36), and because application of filtration during data extraction and application of mixed-effects modelling for statistical analyses minimized the impact of unbalanced observations and inter-individual differences in measures of HR.

Conclusion

This study is the first to examine the association between longitudinal real-world human HRs with multidimensional characteristics of the ambient acoustic environment. Our results indicate that ambient sound intensity is positively associated with heart rates. In addition, we

document that the real-world ambient signal-to-noise ratios are associated with lowered HRs, suggesting that sound conditions which reduce the auditory perceptual load and listening effort de-stress the human cardiovascular system (34,55,56,62). This finding is supported by a documented effect of soundscape on the strength of the association between acoustic characteristics and ANS reactions. That is, in favorable listening conditions, acoustic characteristics have the strongest association with changes in HR.

In summary, our findings suggest a possible mixed influence of everyday sounds on cardiovascular stress, and that the relationship is more complex than is seen from examination of sound intensity alone. Furthermore, our findings highlight the importance of including exposure to ambient acoustics to models predicting human physiology and demonstrate that data logging with commercially available devices can be used to study how ecologically-valid everyday acoustic environments impact and human physiological reactions.

References

1. Flamme GA, Stephenson MR, Deiters K, Tatro A, van Gessel D, Geda K, et al. Typical noise exposure in daily life. Int J Audiol [Internet]. 2012 Feb [cited 2019 Oct 28];51(sup1):S3–11. Available from: http://www.tandfonline.com/doi/full/10.3109/14992027.2011.635316

2. Kirchner DB, Evenson E, Dobie RA, Rabinowitz P, Crawford J, Kopke R, et al. Occupational noise-induced hearing loss: ACOEM task force on occupational hearing loss. J Occup Environ Med [Internet]. 2012;54(1):106–108. Available from: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.593.6717&rep=rep1&type=pdf

3. Kujawa SG. Acceleration of Age-Related Hearing Loss by Early Noise Exposure: Evidence of a Misspent Youth. J Neurosci [Internet]. 2006 Feb 15 [cited 2020 Jan 6];26(7):2115–23. Available from: http://www.jneurosci.org/cgi/doi/10.1523/JNEUROSCI.4985-05.2006

4. Burns K, Sun K, Fobil J, Neitzel R. Heart Rate, Stress, and Occupational Noise Exposure among Electronic Waste Recycling Workers. Int J Environ Res Public Health [Internet]. 2016 Jan 19 [cited 2019 Oct 28];13(1):140. Available from: http://www.mdpi.com/1660-4601/13/1/140

5. Munzel T, Gori T, Babisch W, Basner M. Cardiovascular effects of environmental noise exposure. Eur Heart J [Internet]. 2014 Apr 1 [cited 2019 Oct 21];35(13):829–36. Available from: https://academic.oup.com/eurheartj/article-lookup/doi/10.1093/eurheartj/ehu030

6. WHO/Europe | Biological mechanisms related to cardiovascular and metabolic effects by environmental noise (2018) [Internet]. [cited 2020 Nov 8]. Available from: https://www.euro.who.int/en/health-topics/environment-and-health/noise/publications/2018/biological-mechanisms-related-to-cardiovascular-and-metabolic-effects-by-environmental-noise

7. Belojevic G, Jakovljevic B, Stojanov V, Paunovic K, Ilic J. Urban road-traffic noise and blood pressure and heart rate in preschool children. Environ Int [Internet]. 2008 Feb [cited 2020 Jan 6];34(2):226–31. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0160412007001493

8. Björ B, Burström L, Karlsson M, Nilsson T, Näslund U, Wiklund U. Acute effects on heart rate variability when exposed to hand transmitted vibration and noise. Int Arch Occup Environ Health. 2007 Nov;81(2):193–9.

9. Robinson BF, Epstein SE, Beiser GD, Braunwald E. Control of Heart Rate by the Autonomic Nervous System: Studies in Man on the Interrelation Between Baroreceptor Mechanisms and Exercise. Circ Res [Internet]. 1966 Aug [cited 2020 Jan 7];19(2):400–11. Available from: https://www.ahajournals.org/doi/10.1161/01.RES.19.2.400

10. Tzaneva L, Danev S, Nikolova R. Investigation of noise exposure effect on heart rate variability parameters. Cent Eur J Public Health. 2001 Aug;9(3):130–2.

11. Draghici AE, Taylor JA. The physiological basis and measurement of heart rate variability in humans. J Physiol Anthropol [Internet]. 2016 Dec [cited 2020 Jun 29];35(1):22. Available from: http://jphysiolanthropol.biomedcentral.com/articles/10.1186/s40101-016-0113-7

12. Berger RD, Saul JP, Cohen RJ. Transfer function analysis of autonomic regulation. I. Canine atrial rate response. Am J Physiol-Heart Circ Physiol [Internet]. 1989 Jan 1 [cited 2020 Jun 29];256(1):H142–52. Available from: https://www.physiology.org/doi/10.1152/ajpheart.1989.256.1.H142

13. Glick G, Braunwald E, Lewis RM. Relative Roles of the Sympathetic and Parasympathetic Nervous Systems in the Reflex Control of Heart Rate. Circ Res [Internet]. 1965 Apr [cited 2020 Oct 28];16(4):363–75. Available from: https://www.ahajournals.org/doi/10.1161/01.RES.16.4.363

14. Lusk SL, Gillespie B, Hagerty BM, Ziemba RA. Acute Effects of Noise on Blood Pressure and Heart Rate. Arch Environ Health Int J [Internet]. 2004 Aug [cited 2020 Jan 6];59(8):392–9. Available from: http://www.tandfonline.com/doi/abs/10.3200/AEOH.59.8.392-399

15. Babisch W. Updated exposure-response relationship between road traffic noise and coronary heart diseases: a meta-analysis. Noise Health. 2014 Feb;16(68):1–9.

16. Evans GW, Johnson D. Stress and open-office noise. J Appl Psychol [Internet]. 2000 [cited 2020 Jun 29];85(5):779–83. Available from: http://doi.apa.org/getdoi.cfm?doi=10.1037/0021-9010.85.5.779

17. Shoushtarian M, Weder S, Innes-Brown H, McKay CM. Assessing hearing by measuring heartbeat: The effect of sound level. Yasin I, editor. PLOS ONE [Internet]. 2019 Feb 28 [cited 2019 Dec 16];14(2):e0212940. Available from: http://dx.plos.org/10.1371/journal.pone.0212940

18. Graham FK, Clifton RK. Heart-rate change as a component of the orienting response. Psychol Bull [Internet]. 1966 [cited 2020 Jun 29];65(5):305–20. Available from: http://doi.apa.org/getdoi.cfm?doi=10.1037/h0023258

19. Rajendra Acharya U, Paul Joseph K, Kannathal N, Lim CM, Suri JS. Heart rate variability: a review. Med Biol Eng Comput [Internet]. 2006 Dec 1 [cited 2020 Oct 24];44(12):1031–51. Available from: https://doi.org/10.1007/s11517-006-0119-0

20. Umemura M, Honda K. Influence of music on heart rate variability and comfort--a consideration through comparison of music and noise. J Hum Ergol (Tokyo). 1998 Dec;27(1–2):30–8.

21. Gang MJ, Teft L. Individual Differences in Heart Rate Responses to Affective Sound. Psychophysiology [Internet]. 1975 Jul [cited 2020 Jan 6];12(4):423–6. Available from: http://doi.wiley.com/10.1111/j.1469-8986.1975.tb00016.x

22. Peelle JE. Listening Effort: How the Cognitive Consequences of Acoustic Challenge Are Reflected in Brain and Behavior. Ear Hear [Internet]. 2018 [cited 2020 Oct 30];39(2):204–14. Available from: http://journals.lww.com/00003446-201803000-00004

23. Holube I, Haeder K, Imbery C, Weber R. Subjective Listening Effort and Electrodermal Activity in Listening Situations with Reverberation and Noise. Trends Hear [Internet]. 2016 Sep [cited 2019 Jul 3];20:233121651666773. Available from: http://journals.sagepub.com/doi/10.1177/2331216516667734

24. Richter M. The Moderating Effect of Success Importance on the Relationship Between Listening Demand and Listening Effort: Ear Hear [Internet]. 2016 [cited 2020 Oct 28];37:111S-117S. Available from: http://journals.lww.com/00003446-201607001-00013

25. Pichora-Fuller MK, Kramer SE, Eckert MA, Edwards B, Hornsby BWY, Humes LE, et al. Hearing Impairment and Cognitive Energy: The Framework for Understanding Effortful Listening (FUEL). Ear Hear [Internet]. 2016 [cited 2020 Oct 28];37:5S-27S. Available from: http://journals.lww.com/00003446-201607001-00002

26. Di Nisi J, Muzet A, Ehrhart J, Libert JP. Comparison of Cardiovascular Responses to Noise During Waking and Sleeping in Humans. Sleep [Internet]. 1990 Mar [cited 2020 Jan 6];13(2):108–20. Available from: https://academic.oup.com/sleep/article-lookup/doi/10.1093/sleep/13.2.108

27. El Aarbaoui T, Chaix B. The short-term association between exposure to noise and heart rate variability in daily locations and mobility contexts. J Expo Sci Environ Epidemiol [Internet]. 2019 Aug 12 [cited 2019 Oct 3]; Available from: http://www.nature.com/articles/s41370-019-0158-x

28. Can A, Aumond P, Michel S, DE COENSEL B, Ribeiro C, Botteldooren D, et al. Comparison of noise indicators in an urban context. In: Inter-Noise 2016, 45th International Congress and Exposition of Noise Control Engineering [Internet]. HAMBOURG, Germany; 2016. p. 9p. Available from: https://hal.archives-ouvertes.fr/hal-01373857

29. Nilsson ME, Berglund B. Soundscape Quality in Suburban Green Areas and City Parks [Internet]. 2006 [cited 2019 Dec 19]. Available from: https://www.ingentaconnect.com/content/dav/aaua/2006/00000092/00000006/art00008

30. Schafer RM. The soundscape: Our sonic environment and the tuning of the world. Simon and Schuster; 1993.

31. Long M. Fundamentals of Acoustics. In: Architectural Acoustics [Internet]. Elsevier; 2014 [cited 2020 Jun 11]. p. 39–79. Available from: https://linkinghub.elsevier.com/retrieve/pii/B9780123982582000027

32. Elliott TM, Theunissen FE. The Modulation Transfer Function for Speech Intelligibility. Friston KJ, editor. PLoS Comput Biol [Internet]. 2009 Mar 6 [cited 2020 Jun 12];5(3):e1000302. Available from: https://dx.plos.org/10.1371/journal.pcbi.1000302

33. Brown VA, Strand JF. Noise increases listening effort in normal-hearing young adults, regardless of working memory capacity. Lang Cogn Neurosci [Internet]. 2019 May 28 [cited 2020 Oct 20];34(5):628–40. Available from: https://www.tandfonline.com/doi/full/10.1080/23273798.2018.1562084

34. Picou EM, Gordon J, Ricketts TA. The Effects of Noise and Reverberation on Listening Effort in Adults With Normal Hearing: Ear Hear [Internet]. 2016 [cited 2020 May 5];37(1):1–13. Available from: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00003446-201601000-00001

35. Laplante-Lévesque A, Pontoppidan NH, Mazevski A, Schum D, Behrens T, Porsbo M. Data-driven hearing care with HearingFitness^{TM}: Oticon shares openly its innovative vision and roadmap. Copenhagen, Denmark: Oticon A/S; 2017 p. 1–7. Report No.: 27896UK.

36. Hicks JL, Althoff T, Sosic R, Kuhar P, Bostjancic B, King AC, et al. Best practices for analyzing large-scale health data from wearables and smartphone apps. Npj Digit Med [Internet]. 2019 Dec [cited 2020 Oct 29];2(1):45. Available from: http://www.nature.com/articles/s41746-019-0121-1

37. Witt DR, Kellogg RA, Snyder MP, Dunn J. Windows into human health through wearables data analytics. Curr Opin Biomed Eng [Internet]. 2019 Mar [cited 2020 Oct 29];9:28–46. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2468451118300771

38. Kochkin S. MarkeTrak VIII: The efficacy of hearing aids in achieving compensation equity in the workplace. Hear J. 2010;63(10):19–28.

39. Kates JM. Digital hearing aids. San Diego, Calif.: Plural Publ; 2008. 449 p. (Audiology).

40. Mellor J, Stone MA, Keane J. Application of Data Mining to a Large Hearing-Aid Manufacturer's Dataset to Identify Possible Benefits for Clinicians, Manufacturers, and Users. Trends Hear [Internet]. 2018 Jan [cited 2018 Jul 11];22:233121651877363. Available from: http://journals.sagepub.com/doi/10.1177/2331216518773632

41. Barr DJ, Levy R, Scheepers C, Tily HJ. Random effects structure for confirmatory hypothesis testing: Keep it maximal. J Mem Lang [Internet]. 2013 Apr [cited 2020 Mar 5];68(3):255–78. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0749596X12001180

42. Pinheiro J, Bates D, DebRoy S, Sarkar D, Team RC. nlme: Linear and nonlinear mixed effects models. R Package Version. 2013;3(1):111.

43. Fox J, Weisberg S, Adler D, Bates D, Baud-Bovy G, Ellison S, et al. Package 'car'. Vienna: R Foundation for Statistical Computing. 2012.

44. Fox J, Monette G. Generalized Collinearity Diagnostics. J Am Stat Assoc [Internet]. 1992 Mar 1 [cited 2020 Oct 24];87(417):178–83. Available from: https://www.tandfonline.com/doi/abs/10.1080/01621459.1992.10475190

45. O'brien RM. A Caution Regarding Rules of Thumb for Variance Inflation Factors. Qual Quant [Internet]. 2007 Oct 1 [cited 2020 Oct 24];41(5):673–90. Available from: https://doi.org/10.1007/s11135-006-9018-6

46. Lorah J. Effect size measures for multilevel models: definition, interpretation, and TIMSS example. Large-Scale Assess Educ [Internet]. 2018 Dec [cited 2020 Oct 27];6(1):8. Available

from: https://largescaleassessmentsineducation.springeropen.com/articles/10.1186/s40536-018-0061-2

47. Snijders TA, Bosker RJ. Multilevel analysis: An introduction to basic and advanced multilevel modeling. Sage; 2011.

48. Harrison XA, Donaldson L, Correa-Cano ME, Evans J, Fisher DN, Goodwin CED, et al. A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ [Internet]. 2018 May 23 [cited 2020 Mar 4];6:e4794. Available from: https://peerj.com/articles/4794

49. Humes LE, Rogers SE, Main AK, Kinney DL. The Acoustic Environments in Which Older Adults Wear Their Hearing Aids: Insights From Datalogging Sound Environment Classification. Am J Audiol [Internet]. 2018 Sep 27 [cited 2018 Oct 18];1. Available from: http://aja.pubs.asha.org/article.aspx?doi=10.1044/2018_AJA-18-0061

50. Avram R, Tison GH, Aschbacher K, Kuhar P, Vittinghoff E, Butzner M, et al. Real-world heart rate norms in the Health eHeart study. Npj Digit Med [Internet]. 2019 Dec [cited 2019 Oct 17];2(1):58. Available from: http://www.nature.com/articles/s41746-019-0134-9

51. Gellish RL, Goslin BR, Olson RE, McDONALD A, Russi GD, Moudgil VK. Longitudinal Modeling of the Relationship between Age and Maximal Heart Rate: Med Sci Sports Exerc [Internet]. 2007 May [cited 2020 Oct 24];822–9. Available from: http://journals.lww.com/00005768-200705000-00011

52. Smeds K, Wolters F, Rung M. Estimation of Signal-to-Noise Ratios in Realistic Sound Scenarios. J Am Acad Audiol [Internet]. 2015;26(2):183–96. Available from: https://www.ingentaconnect.com/content/aaa/jaaa/2015/00000026/00000002/art00007

53. Wu Y-H, Stangl E, Chipara O, Hasan SS, Welhaven A, Oleson J. Characteristics of Real-World Signal to Noise Ratios and Speech Listening Situations of Older Adults With Mild to Moderate Hearing Loss. Ear Hear. 2018;39:293–304.

54. Mackersie CL, Calderon-Moultrie N. Autonomic Nervous System Reactivity During Speech Repetition Tasks: Heart Rate Variability and Skin Conductance. Ear Hear [Internet]. 2016 [cited 2020 Jun 22];37:118S-125S. Available from: http://journals.lww.com/00003446-201607001-00014

55. Wendt D, Hietkamp RK, Lunner T. Impact of noise and noise reduction on processing effort: A pupillometry study. J Acoust Soc Am [Internet]. 2017 May 1 [cited 2017 Oct 29];141(5):4040–4040. Available from: http://asa.scitation.org/doi/abs/10.1121/1.4989330

56. Zekveld AA, Koelewijn T, Kramer SE. The Pupil Dilation Response to Auditory Stimuli: Current State of Knowledge. Trends Hear [Internet]. 2018 Jan [cited 2020 Jun 22];22:233121651877717. Available from: http://journals.sagepub.com/doi/10.1177/2331216518777174

57. Seeman S, Sims R. Comparison of Psychophysiological and Dual-Task Measures of Listening Effort. J Speech Lang Hear Res [Internet]. 2015 Dec [cited 2020 Feb 26];58(6):1781–92. Available from: http://pubs.asha.org/doi/10.1044/2015_JSLHR-H-14-0180

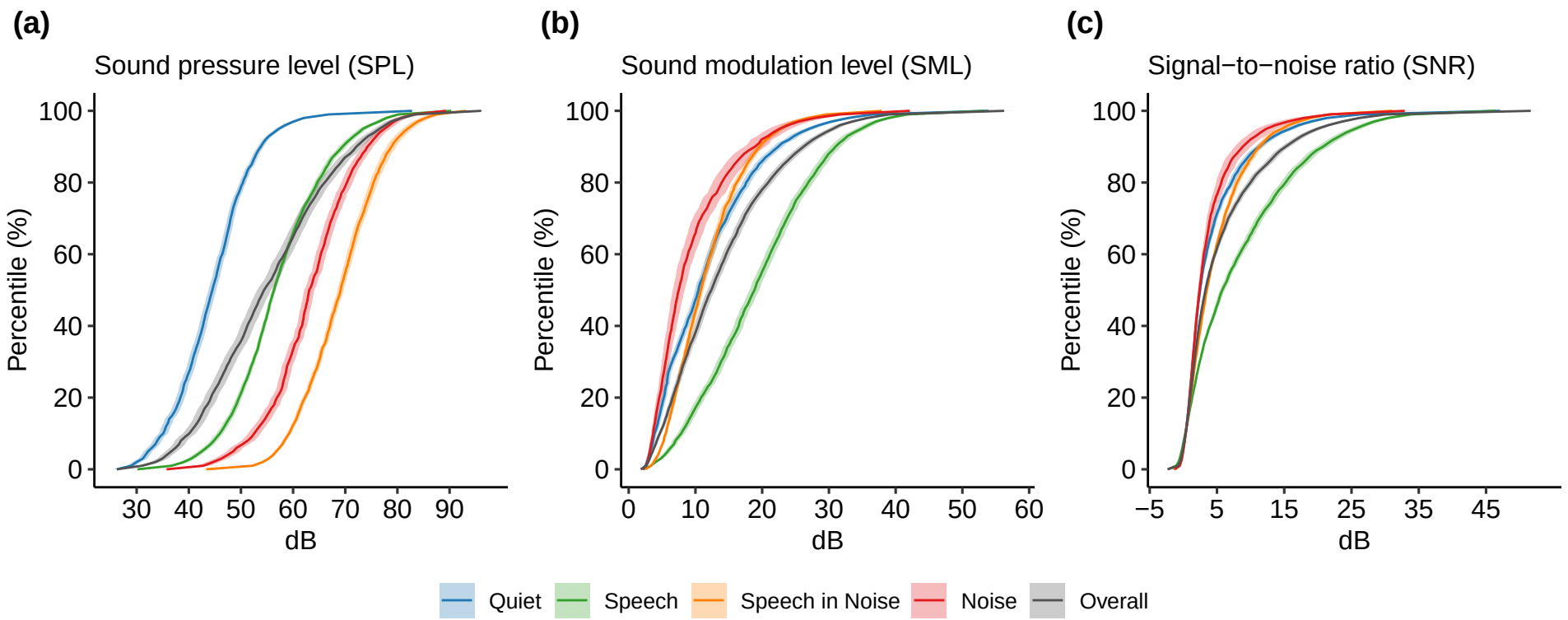
58. Christensen JH, Rossing R, Pontoppidan NH, Anisetti M, Bamiou D-E, Spanoudakis G, et al. Fully synthetic longitudinal real-world data from hearing aid wearers for public health policy modeling. Front Neurosci Audit Cogn Neurosci [Internet]. 2019 Aug 13;13. Available from: https://www.frontiersin.org/articles/10.3389/fnins.2019.00850/full

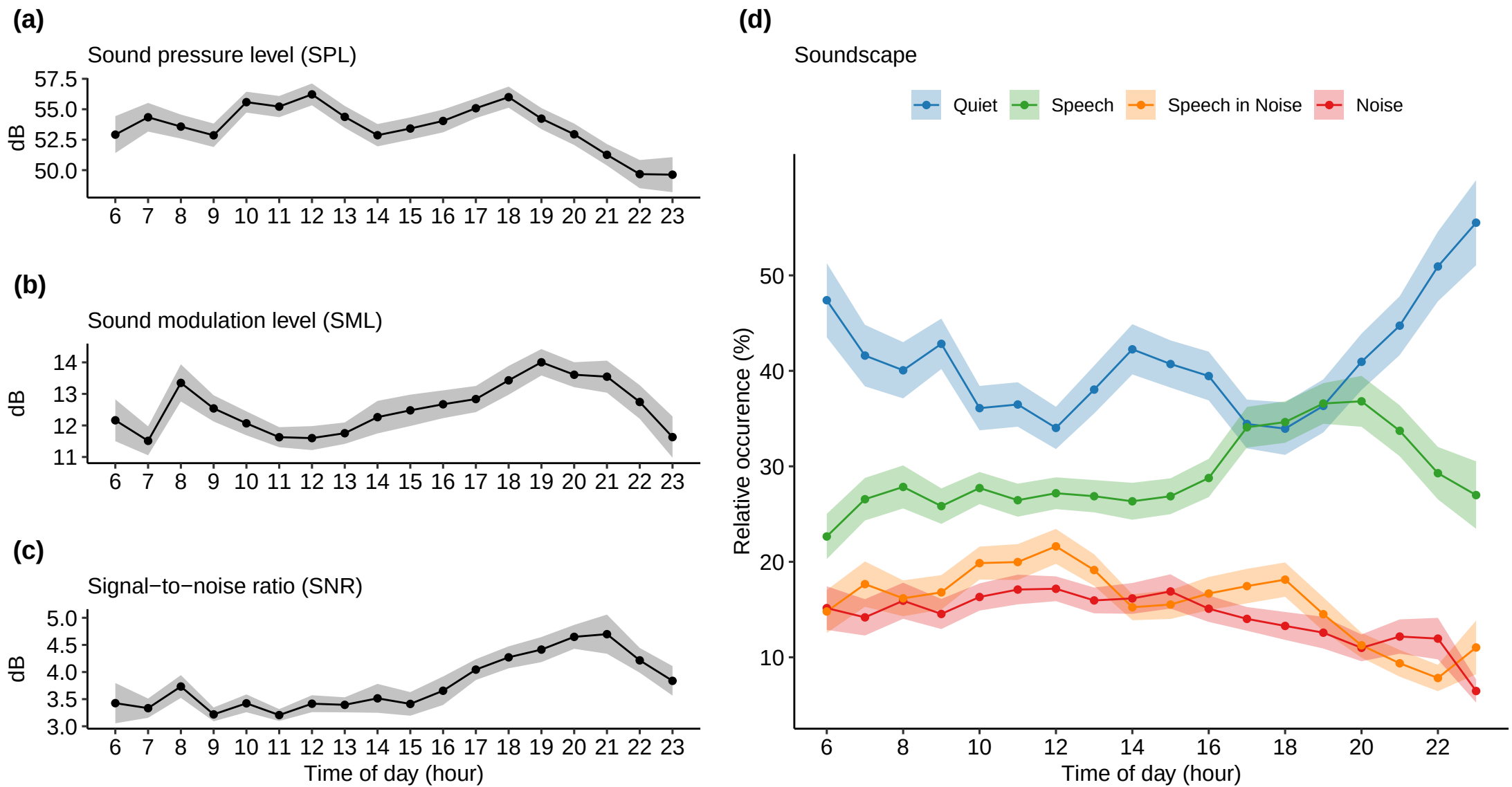
59. Saunders GH, Christensen JH, Gutenberg J, Pontoppidan NH, Smith A, Spanoudakis G, et al. Application of Big Data to Support Evidence-Based Public Health Policy Decision-Making for Hearing: Ear Hear [Internet]. 2020 Jan [cited 2020 Feb 19];1. Available from: http://journals.lww.com/10.1097/AUD.0000000000000850

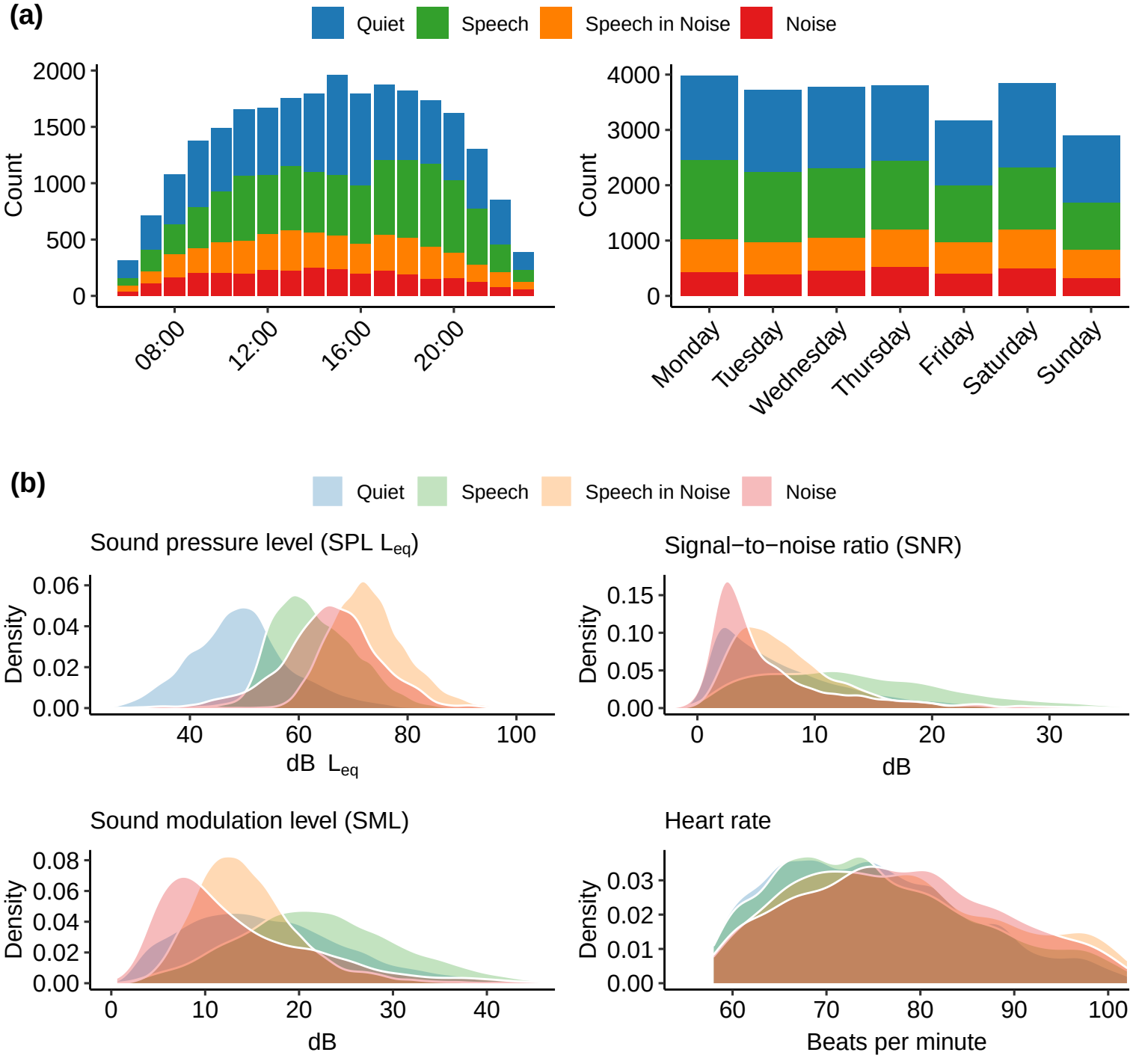
60. Wu Y-H, Bentler RA. Do Older Adults Have Social Lifestyles That Place Fewer Demands on Hearing? J Am Acad Audiol [Internet]. 2012 Oct 1 [cited 2020 May 20];23(9):697–711. Available from: http://openurl.ingenta.com/content/xref?genre=article&issn=1050-0545&volume=23&issue=9&spage=697

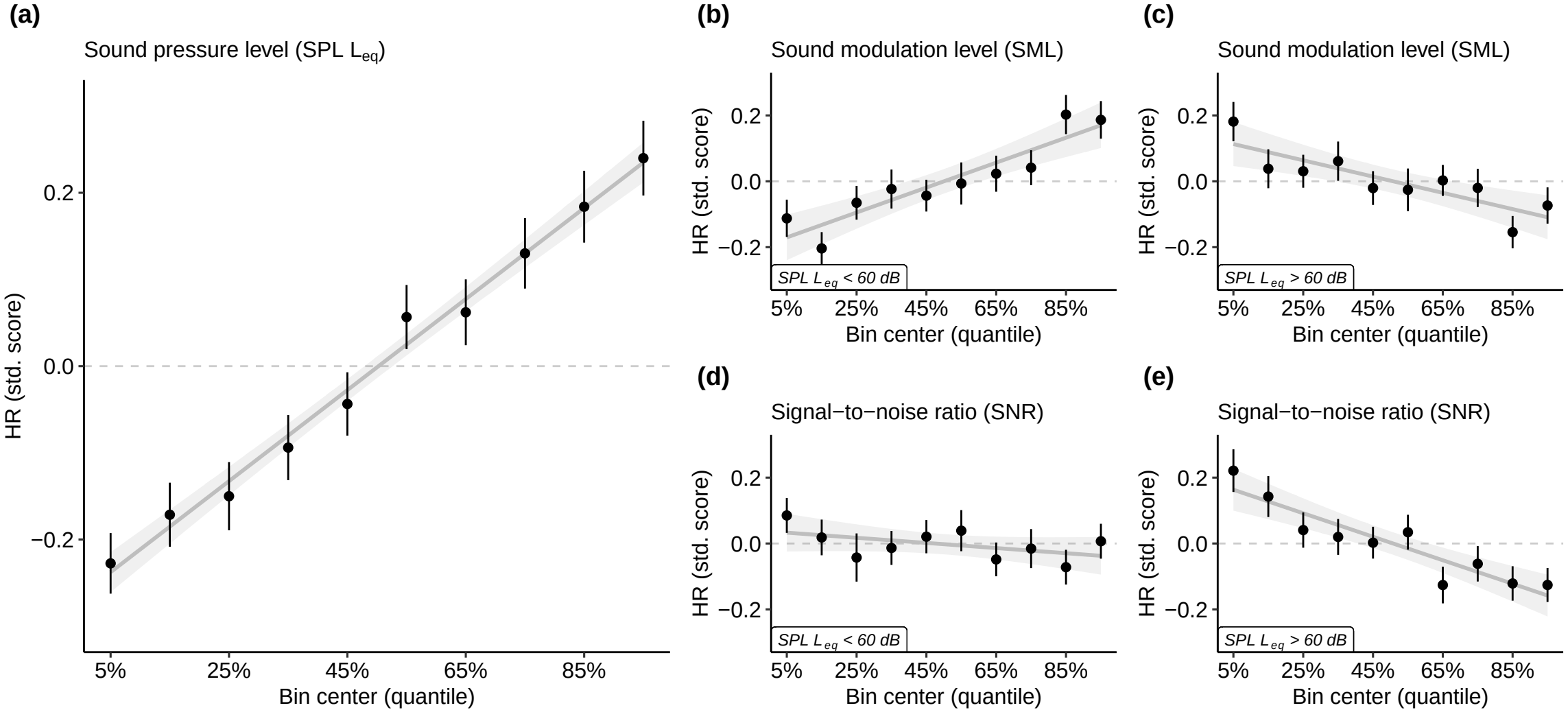
61. Sinnreich R, Kark JD, Friedlander Y, Sapoznikov D, Luria MH. Five minute recordings of heart rate variability for population studies: repeatability and age–sex characteristics. Heart [Internet]. 1998 Aug 1 [cited 2020 Oct 24];80(2):156–62. Available from: https://heart.bmj.com/content/80/2/156

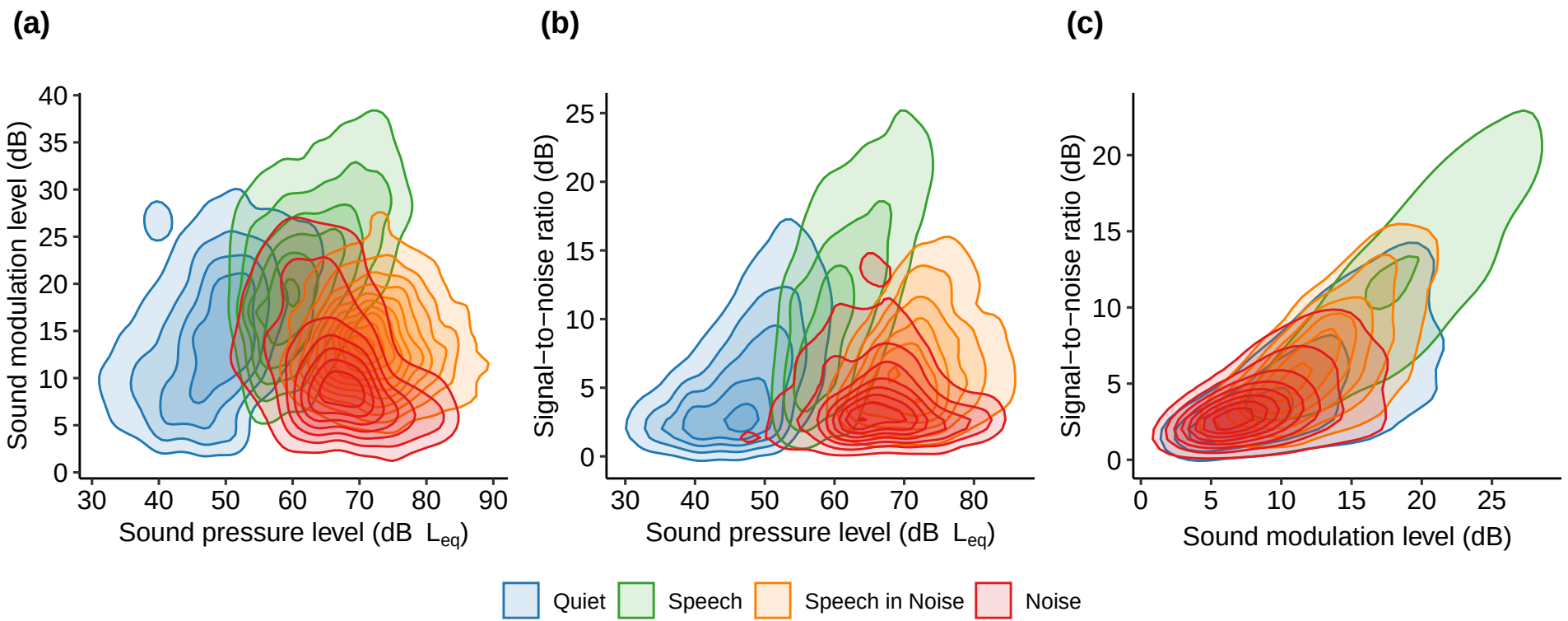
62. Howard CS, Munro KJ, Plack CJ. Listening effort at signal-to-noise ratios that are typical of the school classroom. Int J Audiol [Internet]. 2010 Dec [cited 2020 May 5];49(12):928–32. Available from: http://www.tandfonline.com/doi/full/10.3109/14992027.2010.520036

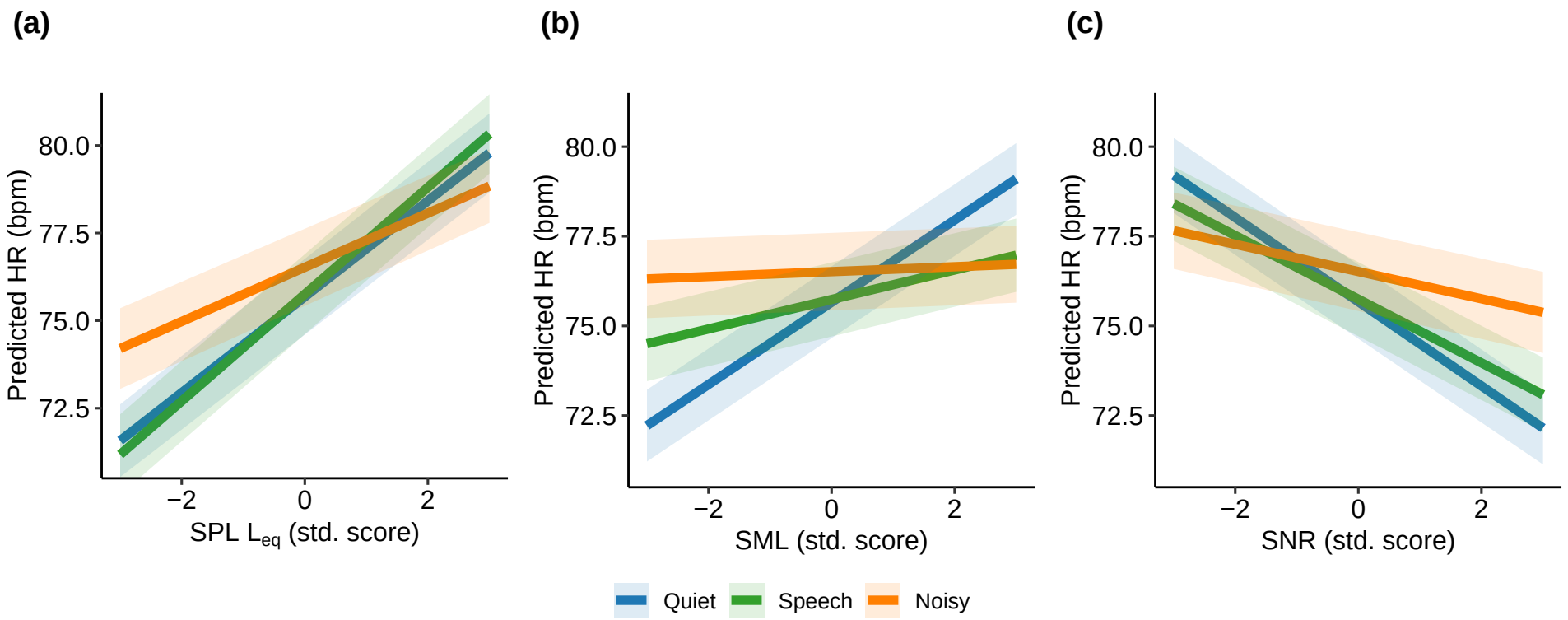

(a)
Sound pressure level (SPL)
Percentile (%)
100
80
60
40
20
0
30
40
50
60
70
80
90
dB
(b)
Sound modulation level (SML)
Percentile (%)
100
80
60
40
20
0
0
10
20
30
40
50
60
dB
(c)
Signal−to−noise ratio (SNR)
Percentile (%)
100
80
60
40
20
0
−5
5
15
25
35
45
dB
Quiet
Speech
Speech in Noise
Noise
Overall


(a)
Sound pressure level (SPL)
dB
57.5
55.0
52.5
50.0
6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
(b)
Sound modulation level (SML)
dB
14
13
12
11
6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
(c)
Signal−to−noise ratio (SNR)
dB
5.0
4.5
4.0
3.5
3.0
6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
Time of day (hour)
(d)
Soundscape
Quiet
Speech
Speech in Noise
Noise
Relative occurence (%)
50
40
30
20
10
6 8 10 12 14 16 18 20 22
Time of day (hour)


(a)
Quiet
Speech
Speech in Noise
Noise
Count
2000
1500
1000
500
0
08:00
12:00
16:00
20:00
4000
3000
2000
1000
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
(b)
Quiet
Speech
Speech in Noise
Noise
Sound pressure level (SPL L_{eq})
Density
0.06
0.04
0.02
0.00
40
60
80
100
dB L_{eq}
Signal−to−noise ratio (SNR)
0.15
0.10
0.05
0.00
0
10
20
30
dB
Sound modulation level (SML)
0.08
0.06
0.04
0.02
0.00
0
10
20
30
40
dB
Heart rate
0.03
0.02
0.01
0.00
60
70
80
90
100
Beats per minute


(a)
Sound pressure level (SPL L_{eq})
HR (std. score)
0.2
0.0
−0.2
5%
25%
45%
65%
85%
Bin center (quantile)
(b)
Sound modulation level (SML)
HR (std. score)
0.2
0.0
−0.2
SPL L_{eq} < 60 dB
5%
25%
45%
65%
85%
Bin center (quantile)
(c)
Sound modulation level (SML)
HR (std. score)
0.2
0.0
−0.2
SPL L_{eq} > 60 dB
5%
25%
45%
65%
85%
Bin center (quantile)
(d)
Signal−to−noise ratio (SNR)
HR (std. score)
0.2
0.0
−0.2
SPL L_{eq} < 60 dB
5%
25%
45%
65%
85%
Bin center (quantile)
(e)
Signal−to−noise ratio (SNR)
HR (std. score)
0.2
0.0
−0.2
SPL L_{eq} > 60 dB
5%
25%
45%
65%
85%
Bin center (quantile)


(a)
(b)
(c)
Sound modulation level (dB)
Signal−to−noise ratio (dB)
Signal−to−noise ratio (dB)
Sound pressure level (dB L_{eq})
Sound pressure level (dB L_{eq})
Sound modulation level (dB)
Quiet
Speech
Speech in Noise
Noise


(a)
(b)
(c)
Predicted HR (bpm)
80.0
77.5
75.0
72.5
−2
0
2
SPL L_{eq} (std. score)
SML (std. score)
SNR (std. score)
Quiet
Speech
Noisy