Everyday sound exposure and the association with human heart rate: evidence from real-world data logging

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Abstract

Prolonged acoustic noise negatively affects human cardiovascular health. However, noise is typically defined by acoustic intensity (i.e. pressure levels) alone, which neglect other dimensions of the sound associated with e.g. the ease of listening.

In this study, we used in-market data from hearing aid users to investigate the longitudinal association between multidimensional characteristics of everyday sound logged by the hearing aids and continuous mean heart rate measures logged by the user's own wearable.

We find that increases in ambient sound 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, we find that 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. In addition, our findings highlight the importance of including environmental sounds to models predicting human physiology.

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

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 when commuting), but despite environmental sounds being an integral part of everyday human life, there is very little knowledge about how aspects of the soundscape encountered in everyday life (beyond the intensity component, Flamme et al., 2012) affect the human body. There is, however, an increasing recognition of the harmful effects on human auditory (Kirchner et al., 2012; Kujawa, 2006) and cardiovascular systems from sounds classified as noise, in particular occupational noise, and noise exceeding certain intensity levels but below those known to cause physical damage to hair cells (Burns et al., 2016; Munzel et al., 2014). A recent report from the WHO summarizes the biological mechanism of cardiovascular reactions to noise (M. Nilsson, 2018). In brief, it suggests that auditory noise causes a direct (i.e. through subcortical connections of the brain) 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 (Belojevic et al., 2008; Björ et al., 2007; M. Nilsson, 2018; Robinson et al., 1966; Tzaneva et al., 2001). This can have acute effects that lead to momentarily elevated heart rate (HR) or blood pressure (Lusk et al., 2004), or cause long-term damage, such as elevating the risk for heart disease due to sustained periods of hypertension (Babisch, 2014).

A recent laboratory study by Shoushtarian et al., (2019) documented a causal link between immediate noise exposure and acute cardiovascular system reactions (Shoushtarian et al., 2019). The study found that noise segments exceeding intensities of 40 dBA significantly increase HRs from baseline within 2 – 5 seconds post exposure. This timing is in line with the dynamic response of sympathetic ANS modulation of HR (Berger et al., 1989), which is considerably slower than the fast acting parasympathetic control (Draghici & Taylor, 2016), suggesting that auditory noise

induces a “fight and flight” stress response in the sympathetic nervous system branch (Munzel et al., 2014). The increase in HRs with noise was reported for intensities up to 90 dBA. However, the reported increase in HRs between 65 dBA and 90 dBA was not significant, suggesting a possible ceiling effect. Interestingly, the study by Shoushtarian et al., (2019) also revealed that low-intensity noise near the threshold for hearing (15 dBA) had a dampening effect on HRs. That is, the low-intensity noise resulted in a 2% reduction in mean HR from baseline levels measured in complete quiet. The authors believe this effect might be due to a fast-acting orienting response caused by the sound onset at low intensities (Graham & Clifton, 1966). Nevertheless, their finding suggests that noise can have diverse effects on the ANS depending on its intensity.

Along those lines, Sim C. S., et al., (2015) reported that noise with equal intensity in decibels but of different type (e.g. traffic noise, background noise, speech noise) had distinct effects on the ANS measured by heart rate variability (HRV). Specifically, they argued that speech noise, besides activating a sympathetic stress reaction, also activates the para-sympathetic nervous system leading to a more stable balance of the ANS. In addition, effects of noise are not always perceivable. In a study by Evans & Johnson (2000), cleric workers exposed to simulated open-office noise showed increased levels of adrenaline, indicative of increased sympathetic levels, compared to a control group, but did not rate perceive levels of stress higher than the control group.

Diverse ANS reactions to sound exposure have also been linked to psychological evaluation. Umemura M. & Honda K., (1998) 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 (Umemura & Honda, 1998). On top of this, individual differences in

HR responses to unpleasant noise (high speed dental engine) have been explained by subjects' familiarity and subjective experience with the acoustic stimuli (Gang & Teft, 1975), indicating a certain adaptation to typically occurring noise sources in daily life.

Measurements of the association between human ANS balance and noise intensity are typically performed under controlled conditions (e.g. in laboratories). This neglects 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 or location (e.g. home versus at work) making it hard to generalize the causal effects found in laboratories to real-world situations with complex sound immersion (Di Nisi et al., 1990). Although, in a recent real-world study, El Aarboui & Chaix found that, over a 7-day period, increases in sound intensity levels were associated with a concomitant increase in HR and HRV parameters, but a delayed decrease in the overall HRV (El Aarbaoui & Chaix, 2019), confirming the role of noise intensity in disrupting ANS stability. In addition, they found that the strength of the association between sound intensity levels and changes in HR were significantly moderated by place/mobility contexts, highlighting the relevance of real-world data. However, their study only considered sound intensity, and as reported above, to understand how everyday sound immersion objectively affect the human cardiovascular system (in particularly the ANS balance) and general wellbeing, more dimensions of the sound must be considered (Can et al., 2016; El Aarbaoui & Chaix, 2019). This notion has long been acknowledged in research of soundscapes (Schafer, 1993) such as when city planning (M. E. Nilsson & Berglund, 2006) 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 the sound environment. First, we describe the characteristics of the typical sound environments faced by a population of hearing aid users, and

second, we model how characteristics of the sound environment are associated with changes in HRs throughout the day.

The sound environment is described using four parameters: sound pressure level (SPLs), sound modulation level (SMLs), signal-to-noise ratio (SNRs), and soundscape class (SS), 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 (Long, 2014). SMLs represent temporal amplitude modulation - that is, the degree by which the sound wave amplitude oscillates over short-term intervals by e.g. speech (Elliott & Theunissen, 2009). SNRs represent a spectral dimension of the sound by differentiating between background noise levels and signal levels. Finally, SSs represent a qualitative dimension of the sound related to how effortless it is to listen to speech-like sources.

Methods

Participants and Ethics

This study does not require ethical approval according to Danish law. Data were obtained from the commercially available HearingFitness™ program (Laplante-Lévesque et al., 2017), which is offered to users of Oticon A/S internet-connected hearing aids. Thus, participants in this study are in-market hearing aid users. In total, we extracted real-world data from 98 random users from June through 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 with age centered around 74 years, which is the reported mean age of hearing aid owners in 2008 (Kochkin, 2010).

Data sources and Apparatus

Users from the sample all wore Oticon Opn™ hearing aids paired with the Oticon ON™ iOS smartphone app for remote control and logging of sound data from hearing aid microphones. Users were selected for the study based on their using a smartwatches linked with the Apple HealthKit app for automatic and continuous logging of 5-min mean HR.

The HearingFitness™ app stores data on a secure server. When signing up for the HearingFitness™ program via the app, users submit written consent agreeing to use of their anonymous data for research purposes. . In addition, usersconsent to have their GPS location (as a relative measure in meters between each sample) and health data from Apple Health Kit extracted and stored on the secure servers. All data collection and storage are conducted in a “privacy by design” manner in accordance with GDPR.

Variables collected

Besides HR data, sound environment data are logged by the smartphone-connected hearing aids. Data consist of three continuous (acoustic data) 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 dynamical 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). Finally, SNR is calculated as 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”. These soundscapes have been used in the standard fitting software for Oticon Hearing Aids since 2004, and similar soundscape classification from hearing aids have been reported as a potential source for data mining (Mellor et al., 2018). Figure 2 shows distributions of soundscapes against each of the three continuous acoustic data variables.

Data logging

Sound environment data are logged every 60 seconds together with timestamps when the user’s hearing aids are turned on and connected via Bluetooth to an associated smartphone. In addition, the 5-min running mean HR is logged approximately every 7 minutes (observed mean = 7.6 minutes, SD = 2.8 minutes) when a wearable with a pulse sensor is connected to the smartphone.

Data extraction and filtration

We extracted data from 98 users from which we obtained 1,144,785 sound environment data logs, which represents approximately 10,000 hours of bilateral hearing aid use, and 616,893 heart rate logs, which represents approximately 72,000 hours of data from a wearable. We only considered data logged between 05:00 and 24:00 to avoid confounds from night-time logs that are likely collected when neither the hearing aids nor wearables were being worn, Further, we only included users for whom there were at least 100 HR logs.

We examined data in two steps. First, to investigate general sound exposure, we used all the sound data regardless of temporal overlap with HR logs. This was done in order to maximize the data available. Second, for subsequent association analysis, we pre-processed the data to ensure full overlap between sound and HR logs. The pre-processing consisted of selecting time windows of five minutes prior to each HR log and computing the average of each sound data variable within

that window. Thus, the fully overlapping data consists of data records with the value of each sound data variable estimated from the same time window as the running mean HR logs. Note that since HRs are not uniformly distributed, we excluded data records with extreme low (<5% quantile) and high (>95% quantile) HR to avoid potential confounds from low incident HRs. This exclusion of extreme data also ensured normality of residuals from statistical modeling (see comparison in Supplementary Information) but did not affect the order of regression coefficients (Table 1) or the statistical significance of the included statistical models. After pre-processing, our data consisted of 24677 data records from 52 users and 917 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 both hearing aid(s), smart phone, and wearable. Furthermore, users wore their hearing aids for different durations throughout the. 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 5:00 and 24:00 per user across the period covered in the data. The grand average sampling frequency across all 917 user days and hours was 2.2 data records per hour (SD = 2.5) with a peak at 18:00 (2.3 data records per hour, SD = 1.8).

Adjusting for movement

A subset of the dataset containing GPS information associated with each pulse measure was used to assess the possible confounding effect of movement activity on the relationship between heart rates and sound environment data. Movement activity 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. That is, 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:

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

with r being equal to the radius of the earth.

Statistical analysis

Due to the unbalanced (unequal samples per user, day, hour etc.) and hierarchical multi-level nature of the data records, we quantified associations between variables using linear mixed-effects models. The autocorrelation of residuals was addressed with a first-order autoregressive structure, which have previously been shown to improve the goodness-of-fit with similar data (El Aarbaoui & Chaix, 2019), while the random-effects structure adjusted for individual differences in both baseline HR and sensitivity towards each fixed-effect (intercept and slopes), time-of-day (intercepts), and weekday (intercepts) (Barr et al., 2013). We used *R* for statistical analysis and visualizations and used the "nlme" package for implementing linear mixed-effects models. Model diagnostics (see Supplementary Information) were conducted in accordance with recommendations in the literature (Harrison et al., 2018), and we ensured that models adhered to assumptions of normality of residuals and homogeneity of variance among random-effect groups.

Results

Data validation

The most occurring (median) SPL across all users were 54.86 dB (SD = 5.74 dB), which corresponds to a level just below normal conversational speech (~60 dB). The sound exposure varied according to the soundscape classified by the hearing aid (see Figure 1 and 2). For example, as expected, "speech" environments consisted of higher values of raw SNR and SML, while "speech in noise" and "noise" were the loudest (highest SPL). This suggests that the classification of soundscape could be reasonably trusted.

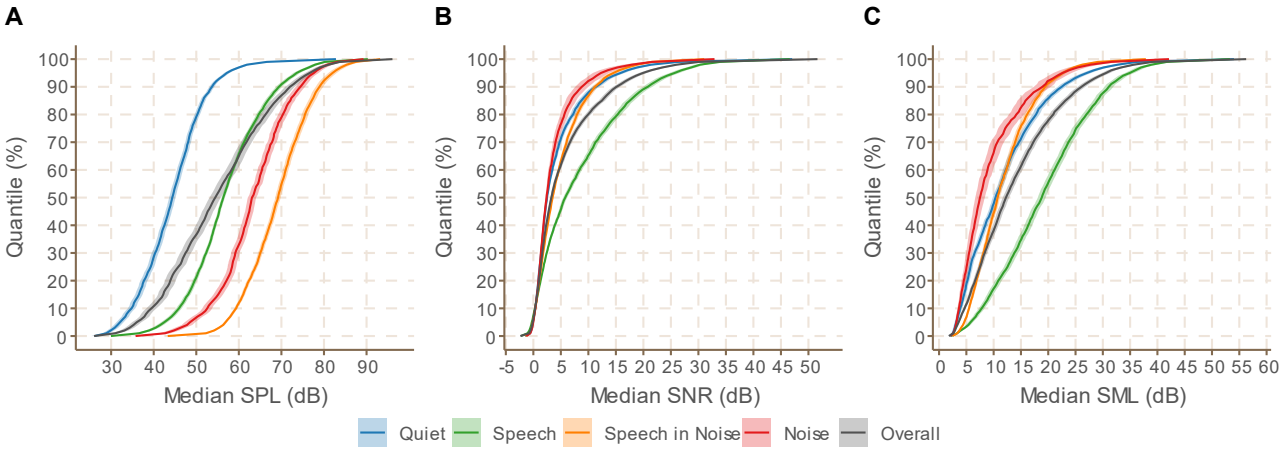

Figure 1: Quantile distributions of raw acoustic data.

We also examined the variation in sound data as a function of time of day. In Figure 2A, each acoustic characteristic is plotted as standard scores, and Figure 2B shows the relative occurrence of each soundscape. As would be expected, the SPL is lowest late at night and early in the morning and the proportion of time the sound environment is classified as being ‘quiet’ is also greatest late at night and early in the morning. Further, the proportion of time sound is classified being ‘speech’ is greatest in the evening, corresponding to the increase in SML in the evening, again, this is to be expected based on the findings of other studies (Humes et al., 2018) and on real life situations.

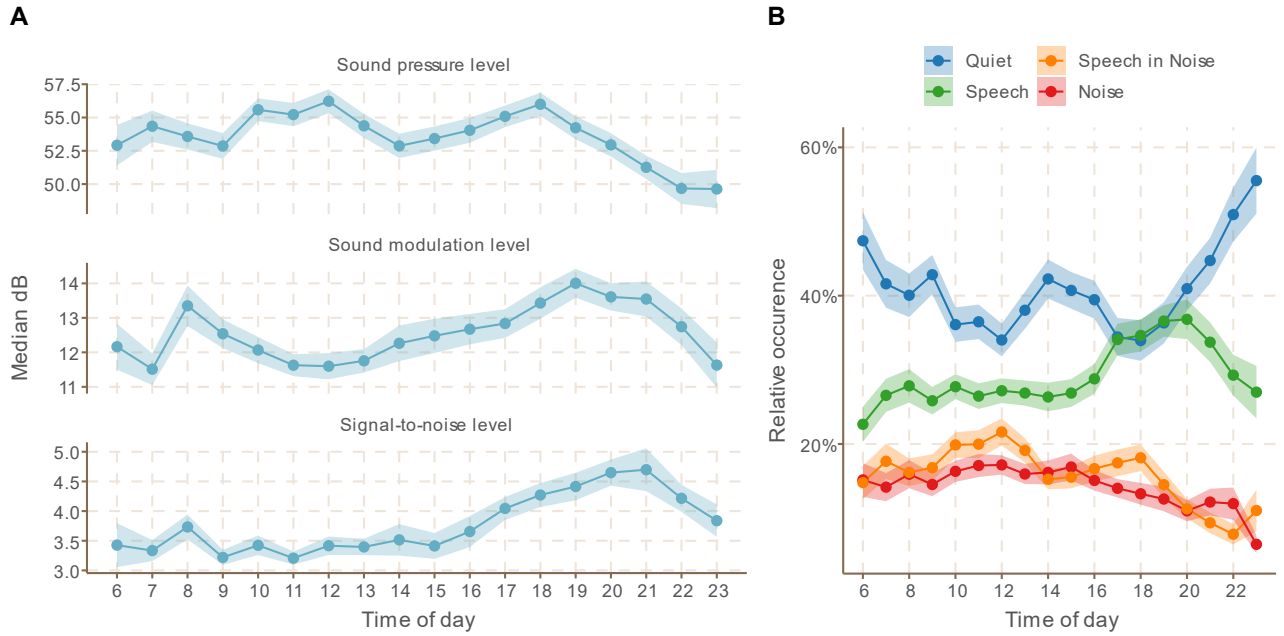

Figure 2: Typical daily sound exposure (A) and most often occurring soundscape (B). Computed as median values across all data for each hour and user and then subsequently taking the median across all users. Shaded area represents the SEM.

Sound environment characteristics fluctuating with time most likely reflects different everyday contexts (e.g. multi-modal peaks in SPL and increased SML and SNR in the evening). In addition, Figure 2B suggests that, besides the hourly fluctuations in soundscape occurrence, approximately 65% – 70% of the day is spent with “quiet” or “speech” soundscapes. For comparison, Humes, L. E. et al., (2018), 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”. In summary, the patterns identified in our sound data document their real-world characteristics and validity.

The grand mean HR was 74.88 bpm (SD = 9.19 bpm). In comparison, real-world HR norms of 66788 individuals spanning all ages above 18 years have been documented to be 79.1 bpm (SD = 14.5), while stratification with age in the range 71 to 80 resulted in a mean HR of 74.2 (SD = 11.1), indicating that users in the current study are indeed of older age (Avram et al., 2019), suggesting that users in the current study are likely to be in this age range. This also agrees with the expected age of the majority of hearing aid users (Kochkin, 2010).

Association between sound and heart rate

Figure 3 shows summary distributions of the data in the data records used for regression analysis). Figure 33A 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, 38% (SD = 20) of data records were registered as belonging to “quiet”, 28% (SD = 17) belonged to “speech”, 17% (SD = 13) belonged to “speech in noise”, and 17% (SD = 12) to “noise” environments.

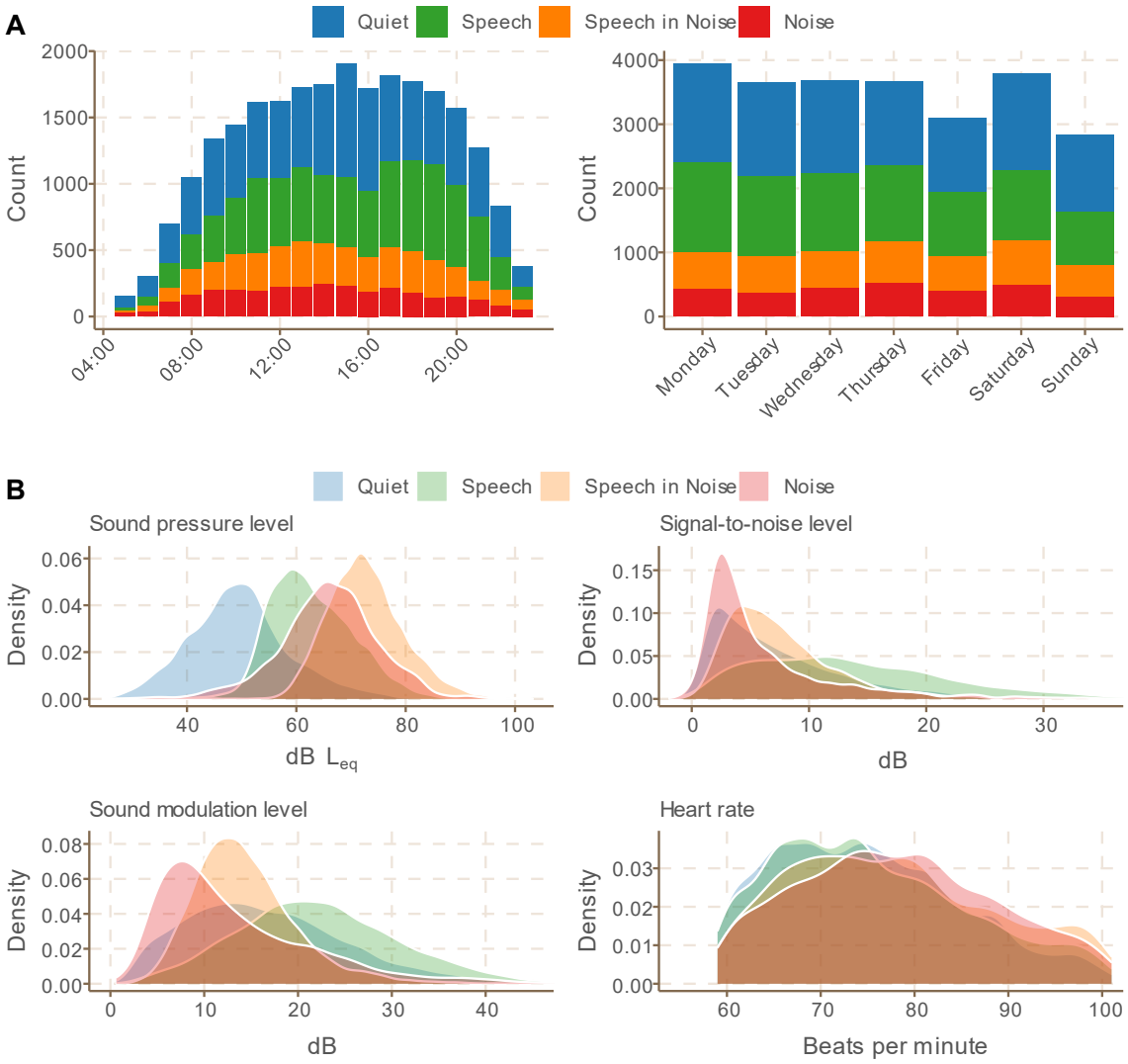

Figure 3: Distribution of combined observations separated by soundscape class and pooled among all users. In A), the total counts of observations are shown across each hour-of-day (left) and weekday (right) for each soundscape class (colors). Note that one observation entails one heart rate measure associated with time-averages of the preceding sound pressure level, signal to noise level, sound modulation level, and soundscape class. In B), density distributions of each of the continuous acoustic variables and heart rate measures are shown.

Density distributions of the continuous acoustic parameters associated with each data record are shown in Figure 33B, three first panels. Not surprisingly, the sound intensity (SPL) were highest for "speech in noise" and "noise" soundscape classes with median SPL L_{eq} equal to 72.3 and 66.2 dBs, respectively. For comparison, the same value in "quiet" was 49.3 dB. On the other hand, "quiet" and "noise" soundscapes exhibited lower median signal to noise ratio (6.0 and 3.9) and modulation

levels (15.7 and 11.0) compared to “speech” (SNR: 12.5, SML: 21.6). The last panel of Figure 3B shows the distribution of HR across all records (excluding the bottom and top 5% most extreme). The grand average HR was 75.8 bpm (SD = 6.5), and separated by soundscape the mean HR was 74.6 bpm (SD = 6.9) for “quiet”, 75.9 bpm (SD = 7.0) for “speech”, 78.2 bpm (SD = 8.6) for “speech in noise”, and 77.6 bpm (SD = 6.9) for “noise”. A repeated measures ANOVA shows these to differ significantly across soundscapes ($F(1.92,94.26) = 10.96$, $p = 0.041$) with post hoc comparisons using Bonferroni correction indicating that the mean heart rate for “quiet” was significantly lower than for “speech” ($p = 0.013$), “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” ($p = 0.041$), and “noise” ($p = 0.019$) while heart rates for “speech in noise” and “noise” did not differ.

Marginal mean HR versus increasing levels of each acoustic characteristic are shown in Figure 4. The marginal mean HR was computed by first standardizing each user’s HR and acoustic data (centering and scaling) and then computing the pooled average HR within non-overlapping bins for quantiles of SPL, SNR and SML (see Figure 5). 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. 60 dB SPL).

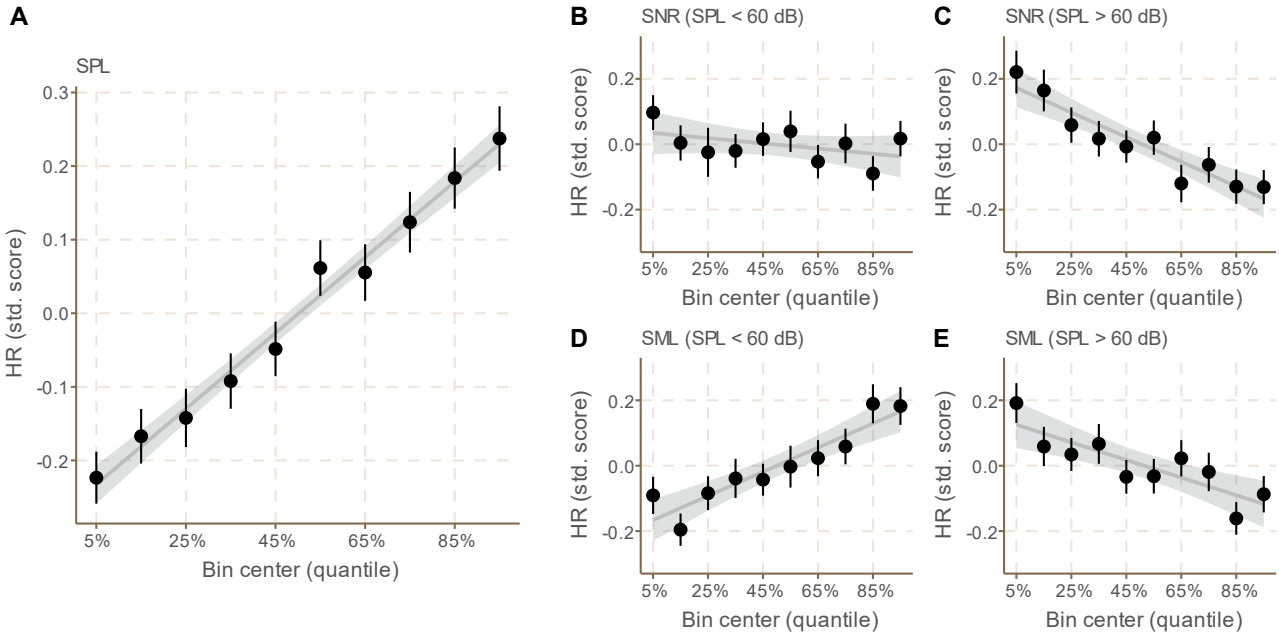

Figure 4: Marginal means of heart rates separated by each acoustic characteristic. Solid lines represent best fitting linear regression. The marginal means were computed separately for observations within quantiles (width 5%) of the acoustic characteristics SPL (A), SNR (B-C), and SML (D-E). In addition, prior to computation of the marginal means, SPL, SNR, SML, and heart rate data were standardized (centered and scaled) for each user individually. In B-E, marginal mean heart rate for increasing levels of SNR and SML are shown for two regions of SPL: low intensity (i.e. SPL < 60 dB) and high intensity (SPL > 60 dB) sound pressure levels, with the threshold based on the overall median observed SPL (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 conditioned on the intensity. That is, SNR seems to be more strongly associated with HR in conditions with high SPL compared to low SPL conditions, whereas SML is either positive or negatively associated with HR again depended on the intensity (i.e. SPL).

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, the different sound dimensions inherently correlate.

For example, high intensity speech signals will also naturally yield a high sound modulation level, and if not masked by noise, also a high SNR. Thus, we assessed the mutual relationships between all sound environment variables to establish a baseline of potential covariance between predictors in statistical modelling. In Figure 55, 2D density distributions as contours are shown for the mutual relation between SPL, SML, SNR, and soundscape class. The most correlated parameters are the SML and SNR (Pearsons' correlation: $r(24675) = 0.72$, $p < 0.001$) since SNR rarely exceeds SML. On the other hand, a wide range of SNR values are observed below any given SML value due to the faster temporal dynamics in the SNR estimate (see *Methods*). The next most correlated relationship was between SPL and SNR (Pearsons' correlation: $r(24675) = 0.37$, $p < 0.001$) while SPL and SML correlated the least (Pearsons' correlation: $r(24675) = 0.14$, $p < 0.001$).

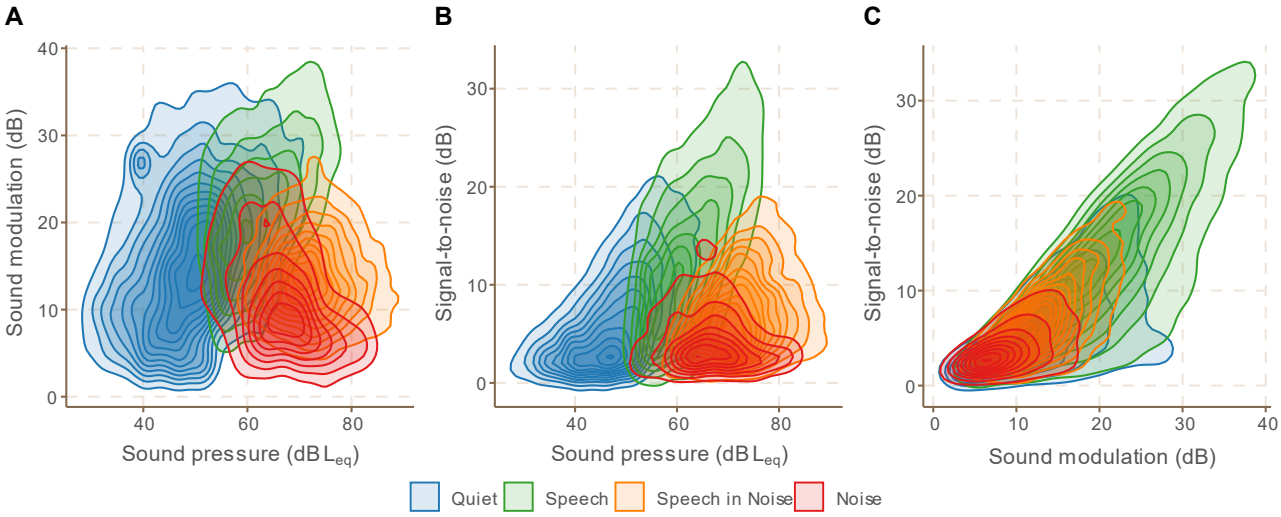

Figure 5: 2D density distributions as contours of each acoustic variable associated with each heart rate log..

Given the high degree of clustering of the continuous acoustic data with soundscape (see Figure 5), we first included the two types of data as independent variables in separate models to predict pulse rates. Thus, the continuous acoustic parameters (SPL, SML, and SN) or the soundscape (contrasted to "Quiet") were included as fixed effects while controlling for individual baseline offsets, time-of-day offsets, and weekday offsets with random intercepts. In addition, when estimating the continuous parameters, individual sensitivity towards each acoustic characteristic were controlled for by random slopes for each user. Furthermore, we fitted the models to a subset of the observations which included GPS data. By this, we investigated the influence of controlling for movement activity estimated from relative GPS coordinates (see next section).

Table 1: Regression coefficients and associated summary statistics for models predicting heart rates (bpm).

	All obs. (n = 24.677)		W. movement (n = 5.991)	
	β	*95% CI*	*β*	95% CI
Soundscape model				
S vs Q	+0.94	[+0.68 to +1.19]	+1.33	[+0.81 to +1.84]
SN vs Q	+1.82	[+1.48 to +2.15]	+1.96	[+1.32 to +2.59]
N vs Q	+2.04	[+1.70 to +2.39]	+2.20	[+1.44 to +2.96]
Acoustic data model				
SPL	+1.31	[+1.07 to +1.55]	+1.33	[+0.88 to +1.77]
SML	+0.57	[+0.37 to +0.77]	+0.47	[+0.10 to +0.85]
SNR	-0.85	[-1.04 to -0.66]	-0.89	[-1.21 to -0.57]

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) = 474, p < 0.001; soundscape data: χ^2 (3) = 174.62, p < 0.001), confirming a significant association between changes in mean HR and the sound environment. This effect was not caused by motion (i.e. sound and HR changing in response to latent physical activity). Models adjusted for the momentary movement activity of users were able to explain additional 32.8% of the HR variance (see Supplementary Information), but had similar regression coefficient values as the un-adjusted models with highly overlapping confidence intervals (see Table 1) indicating that the additional explained variance did not covary with sound data.

The regression coefficients for the soundscape model confirmed the trend present in Figure 3B last panel; HR increase with the complexity of the soundscape going from quiet, to speech, and then

speech in noise and noise. Thus, despite speech in noise being the loudest soundscape (Figure 1A), HRs were overall higher in soundscapes classified as pure noise.

The acoustic data model revealed distinct associations of the HRs with the different acoustic characteristic. Specifically, increasing SPL and SML predicts increasing HRs whereas increasing SNR predicts decreasing HRs.

Moderating effect of soundscape

The outcomes presented in Table 1 suggest that changes in mean HR throughout the day are significantly associated with changes in everyday sounds, and that overall mean HRs are lower in less complex sound environments (e.g. “Quiet” versus “Speech in Noise”). Here, we investigated to what extend the soundscape, classified by the hearing aids, moderated the strength of the association between heart rate and the continuous predictors. 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, less effort is needed to understand speech in “quiet” and “speech” soundscapes than in a “noise” soundscape. Prior to analysis we collapsed across “Speech in Noise” and “Noise” since they were highly overlapping in terms of SPL and SNR (see Figure 5B) and contained the fewest observations (Figure 3A). Thus, the resulting three soundscapes are “Quiet”, “Speech”, and “Noisy” listening conditions, reflecting increasing levels of soundscape complexity.

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 (dAIC = 270.5, chi2(11) = 292.54, p < 0.001) and the acoustic data model (dAIC = 12.6, chi2(8) = 28.6, p < 0.001). Despite the potentially high covariance between soundscape and acoustic data (see Figure 5), the largest variance inflation factor was estimated to be 1.79. The main effects replicated the outcomes of fitting the acoustic data and soundscape models separately (see Table 1). That is, higher HR for more complex soundscape ($\chi^2(2) = 8.03$, $p = 0.018$), more intense and modulated sound environments (SPL: $\chi^2(1) = 58.8$, $p < 0.001$; SML: $\chi^2(1) = 27.1$, $p < 0.001$), and environments with more background noise (SNR: $\chi^2(1) = 53.5$, $p < 0.001$). Additionally, all interactions between soundscape and SPL, SML, and SNR were significant ($\chi^2(2) = 6.7$, $p = 0.035$; $\chi^2(2) = 31.2$, $p < 0.001$; $\chi^2(2) = 10.7$, $p = 0.005$, respectively).

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 (SPL), modulation levels (SML), and signal quality (SNR) when the soundscapes were optimal for listening.

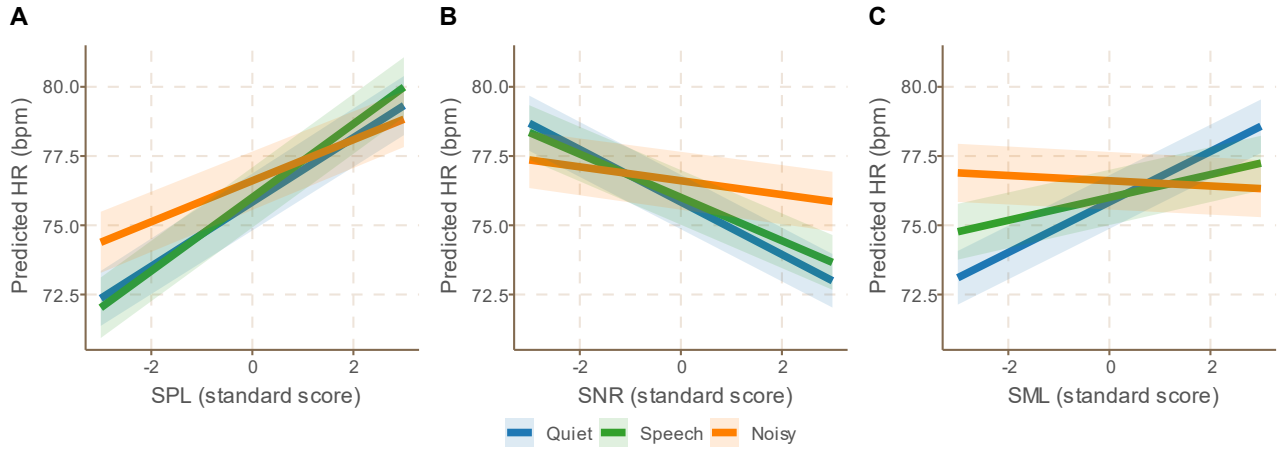

Figure 6: Regression lines from LME interaction model. Shaded area represents the standard error around each prediction.

We assessed the significance of each pairwise interaction by contrasting each coefficient (i.e. slope) with the Quiet soundscape as baseline.

For SPLs (Figure 6A), the slope for "Noisy" soundscape was significantly different (β=-1.38, SE = 0.28, $p < 0.0001$) whereas the slope for "speech" did not differ from the slope for "quiet" (β=-0.12, SE = 0.27, $p = 0.65$). For SNRs (Figure 6B), only the slope for "Noisy" was significantly higher than for "Quiet" (β=0.97, SE = 0.26, $p < 0.001$). Finally, for SMLs (Figure 6C), slopes for both for "Speech" and "Noisy" were significantly lower than for "Quiet" (β=-0.53, SE = 0.18, $p = 0.0037$; β=-0.92, SE = 0.23, $p < 0.001$).

Discussion

Using real-world data from in-market hearing aids we were able to investigate the association between exposure to sound 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 sound exposure from everyday life activities (see Figure 1 and 2), with characteristics of intensity and soundscape occurrences that agree with previous research (Flamme et al., 2012; Humes et al., 2018; Wu et al., 2018).

We find that characteristics of the sound environment are significantly associated with changes in heart rate. Specifically, higher SPLs and SMLs are associated with increased HRe, whereas more favourable (higher) SNRs are associated with lowered HR. In addition, all associations are stronger in simple listening soundscapes (Quiet and Speech) compared to soundscapes classified as containing noise, while marginal means reveal that HR moderation by SMLs and SNRs are distinct depending on the sound intensity (see Figure 4). Specifically, marginal means suggest that the negative association between SNR and mean HR is most pronounced in louder sound environments where the SPL exceeds 60 dB SPL, whereas sound modulation seems to be more strongly associated with increases in HR at intensity levels below 60 dB SPL.

SPLs are directly associated with loudness perception (Long, 2014) and have been found to induce activation of the sympathetic branch of the human ANS (El Aarbaoui & Chaix, 2019; Munzel et al., 2014; Shoushtarian et al., 2019). Our study suggests that even everyday SPLs (i.e. levels well below those typically defined as hazardous to the auditory system) also affect heart rates. Thus, we speculate that the sympathetic ANS branch is moderated by sound pressure - regardless of level of intensity.

We also document a positive, albeit smaller, association between HR and SML. SML indicates how modulated a sound wave is. Highly modulated sound is typically characterized by fast oscillating SPLs which are indicative of e.g. speech or music. We speculate that the positive association between SMLs and HRs are, to some extent, caused by task demands (Mackersie & Calderon-Moultrie, 2016). That is, in highly modulated sound environments, listening and speech demands are increased, which leads to slightly increased sympathetic ANS activity. This speculation is further corroborated by the fact that the positive association between SML and HR is stronger for low-intensity simpler sound environments (i.e. Figure 4D and 6C), which are indicative of task-related activities, compared to loud and noisy environments.

We also document a negative association between real-world HRs and SNRs (see Table 1 and Figure 4 B - C). 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 decrease the parasympathetic ANS activity seen as increased pupil dilation (Wendt et al., 2017; Zekveld et al., 2018) or skin conductance (Mackersie & Calderon-Moultrie, 2016) and decreased HR variability (Seeman & Sims, 2015). 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.

The sound data used in this study are 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 (El Aarbaoui & Chaix, 2019). This highlights a potential for exploiting commercial devices, and in particularly hearing aids, for establishing real-world evidence regarding human behavioural and biological reactions to environmental stimuli. For example, future studies using a similar setup could investigate how sensitivity towards sound exposure potentially differ between populations due to underlying health pathologies. This is further corroborated by the fact that previous research has documented the use of similar hearing aid data logging (Christensen et al., 2019) for policy-making within the hearing or public health domains (Saunders et al., 2020).

Limitations

The users in our dataset are all wearing hearing aids daily thus, they all have some degree of hearing loss and therefore do not represent the general population. Further, the mean age in the

group is likely skewed towards older age. Some studies suggest that the older hearing-impaired people spend more time in quiet sound environments than younger and normal hearing individuals (Wu & Bentler, 2012). Moreover, their sensitivity towards noisy and loud sound environments are expected to differ compared to normal hearing individuals. Finally, the data assessed in the current study is considered real-world in nature, which means that there was no direct control over who used what devices, when, and for how often. However, by both applying filtration during data extraction and pre-processing and using mixed-effects modelling, we minimized the impact of unbalanced observations.

Conclusion

This study is the first to assess longitudinal real-world data of human HRs and multidimensional sound exposure for potential associations. Our results corroborate previously presented laboratory findings (Shoushtarian et al., 2019) and short-term real-world measures (El Aarbaoui & Chaix, 2019), which both indicate that ambient sound intensity is positively associated with heart rates. In addition, we document that the real-world ambient signal-to-noise levels are associated with lowered HRs, suggesting a destressing effect on the human cardiovascular system in conditions assumed to reduce the auditory perceptual load and listening effort (Howard et al., 2010; Picou et al., 2016; Wendt et al., 2017; Zekveld et al., 2018). This finding is furthermore supported by a documented effect of soundscape on the strength of the association between sound 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 sounds to models predicting human physiology. Lastly, our study demonstrates the applicability of data logging using commercially available

devices (here, hearing aids) to establish ecologically valid evidence of everyday sound exposure and human physiological reactions to it.

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