Personal noise exposure during daily commutes and subjectively reported stress: A trip stage level analysis of MobiliSense data

Alex Limin Wang, Sanjeev Bista, Arnaud Can, Basile Chaix

Personal noise exposure during daily commutes and subjectively reported stress: a trip stage level analysis of MobiliSense data

Alex Limin Wang,[1] Sanjeev Bista,[1] Arnaud Can,[2] Basile Chaix[1]

[1] Sorbonne Université, INSERM, Institut Pierre Louis d'Epidémiologie et de Santé Publique IPLESP, Nemesis team, Faculté de Médecine Saint-Antoine, 27 rue Chaligny, 75012 Paris, France

[2] UMRAE, Univ Gustave Eiffel, IFSTTAR, CEREMA, F-44344 Bouguenais, France

---

Alex Limin Wang (*corresponding author)*	limin.wang@iplesp.upmc.fr
Sanjeev Bista	sanjeev.bista@iplesp.upmc.fr
Arnaud Can	arnaud.can@univ-eiffel.fr
Basile Chaix	basile.chaix@iplesp.upmc.fr

Abstract

Background: The auditory and non-auditory health effects of noise have long been established in the literature but previous studies have mainly been in the context of occupational risk. Recent research suggests that daily noise exposures occurring during social activities and commute may be associated with higher psychological stress. Our aim was to explore the association between modes of transportation and noise on the one hand and noise exposures and reported stress on the other hand. Although existing literature shows that noise exposure is especially high during commutes, studies on the topic have been sparse due to cost and logistic constraints; furthermore, sample sizes have been small.

Methods: The present study uses data collected on the daily commutes of 253 participants of the Mobilisense cohort study between 2018 and 2020. Personal dosimeters were used to measure noise exposure by frequency bands over a period of 4 days, resulting in a sample of 7800 trip stage windows. Participants reported trip stress levels during an *a posteriori* phone mobility survey on a scale from 1 (no stress) to 7 (significantly stressful conditions). Modes of transportation (metro, car, walking, etc.) were collected from the same mobility survey based on Global Positioning System (GPS) receivers.

Results: While all transport modes resulted in higher exposure to low frequency noise compared to walking, all modes but tramway and driving or being the passenger of a car were associated with an increased exposure to high frequency noise. The LAeq noise indicator (overall noise) was associated with reported stress: for every 10 dB(A) increase in LAeq, individuals reported experiencing 1.118 times (95% confidence interval: 1.067, 1.172) higher levels of stress. Multiple noise indicator models did not show evidence that specific frequency components were associated with stress beyond overall noise.

Conclusion: Our findings suggest that noise exposure during commutes vary according to modes of transportation. Given that noise exposure resulted in higher reported levels of stress, future research should examine transportation noise effects on physiological variables.

Key Words: Noise exposure, transport, stress

Introduction

Noise is a pervasive component of day-to-day life and is associated with both auditory and non-auditory health effects like cardiovascular diseases, diabetes, anxiety and depression (1–5). Existing studies on the causal relationship between noise exposure, noise perception and health have yielded inconsistent findings which may be attributed to conceptual and methodological issues (6). Only a small number of studies have attempted to examine how momentary perceived noise can influence people's subjective perceptions. Bild et al. postulates that a sound is determined to be a "noise" if it interferes with an individual's daily activities and social interactions (7). Other factors, like the time of day when the noise occurs, as well as the duration of the occurrence can also affect noise perception (8,9). Existing studies in the literature also tend to focus on individuals' chronic noise exposure to one specific type of noise from a specific source (e.g. road traffic, railway, or aircraft) usually at one particular geographic location (e.g. school, home, or workplace) (4,10–12). It has also been emphasized that studies tend to focus on noise in residential areas and ignore exposure in public urban areas (16). Indeed, as participants are dynamic in their daily movements (e.g. running errands, buying groceries), they are exposed to multiple sources of noise over various geographic locations for varying amounts of time (13,14). Neglecting the dynamics of individuals' daily movements can lead to a substantial misclassification of the overall exposure (15). Therefore, taking dynamic spatiotemporal data of how individuals interact with their environment helps to establish a more accurate assessment of the relationship between environmental noise exposure and stress (6,17–19).

This study therefore proposes a novel mobility survey strategy based on Global Positioning System (GPS) receivers which decomposes trips into trip stages, and utilizes location information and participants’ confirmation to identify the modes of transportation taken. It also incorporates noise exposure for each trip stage. Based on this novel methodology, the empirical aim of this study was to utilize the accuracy gains offered by this mobility survey to assess (i) how personal exposure to noise (overall and low- and high-frequency noise) varied according to activity patterns and during personal transport activities (i.e. by transportation mode); and (ii) whether personal exposure to noise during trips was associated with the reported stress levels of participants.

Methods

Population

Participants included adults of both genders from the Mobilisense cohort which was recruited using a two-stage stratified sampling design. In the first stage, neighbourhood sampling took place through the random selection of local neighbourhoods in the Metropolitan Area of Paris (Grand Paris). Neighbourhoods were stratified by quartiles of area-level household income as well as by quartiles of road traffic density (using the traffic model from the Ministry of Infrastructure). Within each income area stratum, 30 neighbourhoods were randomly selected in each of the two extreme quartiles of traffic density, resulting in 60 neighbourhoods in each area income quartile and 240 neighbourhoods overall. In the second stage, census information collected by the French National Institute of Statistics and Economic Studies (Insee) was used to sample dwelling units in each of the selected neighbourhoods. This sampling design was useful to maximize disparities in exposure to air pollutants and noise, while allowing us to document deviations from representativity to the background population of the Grand Paris. Overall, 33,501 dwellings were selected from the 240 previously identified neighbourhoods based on the

2013-2014 censuses. Demographic and sociodemographic information on these dwellings was also obtained from the census. Each dwelling was contacted twice by postal mail. Finally, 282 eligible participants aged from 30 to 64 years old were included between May 2018 and March 2020. This age range was selected to reflect a segment of the general adult population in Grand Paris that is both likely to be integrated in professional life (as we wanted to look at trip-level exposure during commutes) and is potentially affected by the onset of chronic diseases. We applied the following inclusion criteria: speaking French, being free of cardiovascular, cerebrovascular or specific contagious pulmonary diseases and glaucoma, not wearing an implanted device, not wearing an auditive device and not having audition problems, not being pregnant and not breastfeeding a child, not being a smoker and not living in a smoking household (for the proper functioning of air pollution sensors), not intending to move outside the Grand Paris area during the 2-year duration of the study, not being a night worker, not working outside the region 4 days or more per week, and not being cognitively impaired.

The participants were recruited at their home after signing an informed consent letter. Prior to sensor-based assessment, participants were guided through pre-study computerized questionnaires which collected information pertaining to dimensions including but not limited to: socioeconomic status, occupational history over 2 years, health-related behaviour (e.g., physical activity, past smoking, etc.), resources for transport (e.g., driving license, public transport pass, etc.), perceptions related to air pollution and noise, etc. Participants carried sensors over a 6 day period and then underwent a GPS-based mobility survey along with a post-questionnaire during a follow-up phone survey. The GPS-based mobility survey targeted the period where the GPS receiver and other sensors where worn. The sampling and data collection protocol of

MobiliSense was approved by the National Council for Statistical Information, the French Data Protection Authority, and the Ethical Committee of Inserm.

Sensor based protocol and mobility survey

Participants wore a Class I equivalent dosimeter SV 104A on their belt with the microphone secured near the ear and on top of clothing for 4 days during their commutes and were instructed to recharge it overnight. Noise dosimeters had three filters available to provide three distinct measurement profiles for sound (20). The three filters (or weightings) A, C, and Z are as follows: A approximates the range of sounds heard by the human ear; C is a standard weighting of the audible frequencies but focuses more on the effect of low-frequency sounds as well as peak sounds resulting from sudden or brief noises (i.e. crashes or bangs) (21) ; Z represents the actual noise that is made with no weighting (Z stands for zero) and ranges from 8Hz to 20kHz. .

Personal dosimeters recorded noise level measurements between 20Hz and 10kHz per second and were calibrated before and after use by each participant following the manufacturer's instructions. In order to account for the natural scope of human hearing which ranges from 20Hz to 20kHz with reduced sensitivity to low and high frequency sounds (below 1kHz and above 4kHz) (22), sound level measurements were "weighted" using A- and C-weightings to produce one second intervals of A- and C-weighted measurements (noted as LAeq,1s and LCeq,1s respectively). In order to take into account noise level fluctuations over a period of time, the "average energy" or Leq value is calculated to produce an energetic mean. The Leq is not a simple arithmetic average as decibels are measured in logarithmic values. It reflects the constant noise level that would have been produced with the same energy rather than the noise actually perceived during the given period.

For each trip stage window, several acoustic indicators were computed. First, the equivalent continuous sound level (Leq) with A- and C-weightings was calculated. Second, we determined so-called spectral indicators for bands of low frequency (20Hz to 125Hz), medium frequency (160Hz to 2kHz) and high frequency (2.5kHz to 20kHz). For each frequency interval, based on the one second A-weighted equivalent continuous sound levels, an energetic mean was calculated for each trip stage to produce LAeq[20Hz-125Hz],$_T$ LAeq[160Hz-2kHz],$_T$ and LAeq[2.5kHz-20kHz],$_T$ These are henceforth referred to as low frequency, medium frequency, and high frequency noises; in this case, the subscript "$_T$" refers to the time period during which the measurement was taken. Third, we calculated LCeq,1s-LAeq,1s noted CA,1s. This difference accounts for low frequency sounds below 1kHz. The average of such difference at the second level was calculated for each trip stage.

Participants also wore a GPS receiver and were asked to complete a travel diary on the places visited and modes of transportation taken as supporting information for the mobility survey, which was carried out a few days after the end of data collection. In order to assess participants' transportation modes and stress reports per trip, GPS tagged commutes were uploaded to Tripbuilder Web, an online application which integrates Google Maps and which automatically generates trip stages from location data and identifies the mode of transportation taken for each trip stage. According to Heshner and Button, trips often involve different modes of transportation (e.g. walking and public transportation), while trip stages refer to the unimodal portions of trips (segments of trips which are based on a unique mode of transportation (23). A purely unimodal trip occurs only if the same mode of transportation is taken from the departure place to the destination without the use of any other modes (including walking).

Once data collection was completed, research assistants used the GPS data and identified trips and transportation modes displayed in the Tripbuilder web mapping application to conduct, with minimal delays after the GPS follow-up, a telephone interview with the participants (mobility survey). Only research assistants had access to the application screen while participants were sent detailed paper screenshots of their GPS trips via postal mail. In addition, the research assistants considered the paper travel diary as supportive information during the telephone mobility survey. Participants were walked through the different days and through each trip stage taken to help facilitate recall. Research assistants confirmed or if necessary, manually edited the type of transportation taken at each trip stage. Participants were also successively asked to report *a posteriori* the level of stress experienced for each trip stage and whether any particular trip stage over that day was more stressful than the others. The data collection steps as well as the type of data collected in each stage are detailed in Figure 1. Stress level was coded on a scale of 1 to 7 for each trip stage. The stress scale corresponds to the following: 1 - Conditions are perfect, no stress; 2/3/4 - Objectively stressful conditions were present, which however did not bother the participant, with a gradation of 2 (mild), 3 (intermediate), and 4 (significant); 5/6/7 - Objectively stressful conditions which stressed the participants slightly (=5), intermediately (=6), and significantly (=7).

It was specified that the sources of discomfort and stress must be linked either to the transport conditions themselves (e.g. traffic jam, cancelled train, crowded metros, etc.) or to the circumstances of the trip (e.g. the person was late, he fell, etc.). A summary sentence was then used to identify stressful trip stages and to pinpoint whether the travel conditions themselves were really the source of stress, such as: "That day, when you took the metro in the morning to go to X, or in the afternoon to go to Y or in the evening to go to Z, were the travel conditions particularly stressful? For example, was the metro crowded? Were there any delays or were you running late?" By the responses given by the participants, research assistants placed the conditions on the stress scale.

Classification of trips

Based on the travel modes indicated in each trip stage, we discerned the following categories: walking only; other active modes (biking, rollerblading, skateboarding, etc.); personal motorized transport (driver); personal motorized transport (passenger); RER/TER/SNCF; bus; metro; tram; and other. RER/TER/SNCF incorporates the RER (higher speed trains travelling to and from the suburbs), TER (trains from Paris towards suburbs or adjacent regions), and SNCF standard suburban trains. Personal motorized vehicles (as a passenger or driver) include both four-wheeled motorized vehicles (including taxis) and two-wheeled motor vehicles. The "other" category incorporates miscellaneous modes like other long-distance trains, plane trips, boats, etc.

Sociodemographic and time-related covariates

Age was coded in 3 categories. Education was coded into 4 categories: no education/primary education/lower secondary education; higher secondary and lower tertiary; intermediate tertiary;

and upper tertiary education. Employment status was classified into 4 categories: stable job; unstable or temporary job; unemployed; and other (e.g. retired). Household income levels were calculated by standardizing average household income by family size (one unit per member ≥14 years, 0.5 unit otherwise) and then divided into quartiles.

With regards to time, our analysis distinguished weekends from weekdays, as well as time of the day (morning: 1:00 am – 9:59 am; day: 10:00 am – 6:59 pm; evening: 7:00 pm 0:59 am).

Statistical analysis

The dataset consisted in the trip stage windows for each participant with corresponding information on the mode of transportation, amount of stress experienced, and the appropriate acoustic indicators.

Objective 1 involved assessing the relationship between transportation modes and noise indicators, using linear mixed effect models. Noise exposure was measured according to the various indicators. Both individual random effect and temporal autocorrelation [AR(1) structure] were included in the linear model. All analyses were performed in R version 1.2.5042 (24). Mixed models were estimated using the nlme package version 2.1-2.131, while plots were made using the ggplot2 package version 2.2.1.

Objective 2 was the assessment of the relationship between noise and stress. A quasi-Poisson model was used to assess the relationship between noise exposure and stress. The quasi-Poisson model was chosen over a Poisson model as there was evidence of overdispersion of the outcome.

The stress variable was transformed into “stress-minus-1” in order to obtain a count variable ranging from 0 to 6 rather than from 1 to 7. Since the outcome was log transformed, the regression coefficients were exponentiated back. This can then be interpreted as multipliers of the stress level for a particular variable. In order to take repeated measurements into account, individual random intercepts were incorporated in the model. Temporal autocorrelation between the repeated measurements within each participant was taken into account by using an autoregressive AR(1) function which assigns a covariance structure with correlation that decreases with increases in time intervals separating the measures for a participant (25,26). Quasi-Poisson models were run using the GLMMadaptive package version 0.6-8 and the MASS package version 7.3-51.4. Root mean square error (RMSE) values were used to compare the fit of models.

Results

Descriptive information on the sample

Among our 282 participants, the noise data collection failed for 17 participants, and another 12 participants lacked noise frequency band data. These participants were excluded, leaving 253 participants for the present analysis. Of the 12994 stages of trips identified for these participants, 4264 were made on days where the protocol did not include a noise data collection. We further excluded 916 trip stages for which noise data were missing, and 14 trip stages for which there was less than 50% of the noise data. We analysed data on 7800 trip stages from 253 participants. Among this final sample, 58% were women; 73% had a permanent job, 13% were retired, and 4% unemployed; and 50% had three or more years of university education.

Overall, 6522 (83.6%) trip stages were reported as being “1” on the stress scale while only 24 (0.31%) were reported as “6” and 14 (0.18%) as “7”. In the distribution of trip stages, 59.3% were entirely walked trips; 5.1% using bikes/roller-skates/skateboards; 2.6% were with buses/coaches, 7.5% with metros, 4.1% with suburban trains, and 1.2% with tramways; and 16.8% and 3.2% involved personal motorized vehicles as the driver or passenger, respectively. The mean duration of trip stages was 12.1 minutes, with the median duration being 6.5 minutes (standard deviation 20.1). The range of the duration of trip stages was 0.05 minutes to 567 minutes.

Modes of transportation and noise exposure

As shown in Figure 2, the median LAeqT exposure was highest for trips involving the metro [median 74.7 dB(A), interdecile range: 65.1, 80.2 dB(A)] while it was lowest for entirely walked trips [median 68.7 dB(A), interdecile range: 54.0, 76.9 dB(A)]. Personal motorized vehicle trip stages taken as the passenger showed the largest range in terms of LAeqT exposure [median 68.9 dB(A), minimum 25.7, maximum 96.9 dB(A)].

As shown in Table 1, mixed effects models were generated for each noise indicator as the outcome, and included participant random effect and temporal autocorrelation, as well as sociodemographic variables as a way of correcting for the sociodemographic distortions in the sample.

Regarding LAeq, individuals in the study experience on average a 5.5 dB(A) (95% CI 4.7, 6.3) increase in noise exposure when taking the metro compared to walking as well as a 4.0 dB(A)

(95% CI 3.0, 5.1) increase when taking suburban trains (RER/TER/SNCF) compared to walked trips. Although to a lower extent, there were also indications of a higher LAeq noise exposure in the bus, in the tram, when driving a car, and with other active modes compared to walking. Furthermore, when compared to walking, all transport modes were associated with a higher exposure to low frequency noise, especially those involving taking the bus and driving a car. All transport modes except for taking the tram or driving a car were related to a higher exposure to high frequency noise when compared to walking, and this is especially true for using the metro.

Relationship between noise exposure and stress

Table 2 reports how the potential confounders were related to the reported stress in trips in quasi-Poisson models. Sociodemographic covariates showed no association. Weekend trips were associated with a lower reported stress while morning trips were related to a higher stress. Certain modes of transportation resulted in higher reported levels of stress. Compared to walked trips, taking the bus/coach led to 1.859 times (95% CI 1.518, 2.277) higher stress levels; metro 1.862 times (95% CI 1.639, 2.114); and RER/TER/SNCF 2.022 times (95% CI 1.724, 2.370) higher stress levels. Using a car as a driver or passenger was also associated with higher levels of stress than walking. However, it is for the other active modes that the reported stress level was the highest, with a ratio of 2.796 (95% CI 2.338, 3.343).

Table 3 presents the associations between noise exposure (6 different indicators) and subjective stress, adjusted for the variables reported in Table 2. In order to test whether noise indicators were nonlinearly associated with stress, quadratic terms were also added into the model. However, as there was no evidence of quadratic patterns, the squared noise indicator terms were dropped from the models. In 1-indicator models, for every 10 dB(A) increase in LAeqT, the level of reported stress was shown to increase by 1.118 times (95% CI 1.067, 1.172). Similar trends were observed for the remaining acoustic indicators (except for CA), possibly due to the high correlation between noise indicators (see Figure 3). As a result, r-squared values and the root mean square error (RMSE) indicators among the different models were relatively similar.

We then estimated models for the trip-level stress outcome including the LAeq and each time one additional indicator (bottom of Table 3). In these models, only LAeq remained associated with stress, while all of the other indicators lost their association with the outcome.

Discussion

Summary of findings and interpretation

This study analysed the association between several noise indicators and stress in daily commutes within a real-life setting. We documented disparities in noise exposure across transportation modes. We controlled for sociodemographic factors due to the related distortions in our sample: people from different social and demographic backgrounds typically use different transportation modes and participants included in our small sample may not be representative of their sociodemographic groups in terms of place of residence and transportation modes used. Thus, it was necessary to control for these variables to avoid sample distortions which would affect the transportation modes' effects on exposure and stress. We also controlled for the day of the week and the time of day. Previous studies have indeed found that the subjectivity of noise perception is influenced by the time of day during which the noise occurs (8) and that noise is less likely to be perceived as being “normal” when it occurs at night (between 10:00 p.m. and 8:00 a.m.) compared to when it occurs during the day (9).

A higher overall level of noise exposure was documented in metros and in suburban trains, and to a lower extent in other modes compared to walking. However, our study which assessed personal exposure to low and high noise frequencies brought novel information by showing that exposure to particular noise frequencies also varied by transportation modes. For instance, while taking the bus and driving were associated with particularly higher exposure to low frequency noise compared to walking, using the metro is especially associated with higher exposure to high frequency noise. Contrary to the metro, taking the tram or driving a car were associated with a lower exposure to high frequency noise than walking. The noise at these high frequencies (>2.5kHz) heard in the tram or in a car comes mainly from the outside of the vehicle, which filters out some of the noise. This is different to the metros, which produce a lot more of high frequency, squealing/screeching noises.

In our innovative approach assessing the stress effects of noise by frequency bands, all indicators of noise exposure showed a positive association with trip-level self-reported stress. We controlled for transportation modes and sociodemographic characteristics because the two likely causally influence the noise exposure in trips and also influence stress through other pathways than noise. We did not find evidence that any of our refined noise indicators accounting for frequency bands were associated with stress beyond overall noise. This is in opposition with our a priori expectation that high frequency noise may be particularly stressful.

Strengths and limitations

Regarding strengths, the present study uses newly developed methodologies for the joint collection and processing of GPS, mobility survey, and personal noise exposure data to present an accurate assessment of noise exposure in daily commutes.

In a previous study of ours where we ranked acoustic indicators on the basis of their predictive ability (27), C-weighted acoustic indicators tended to outperform their A-weighted counterparts, despite the fact that A-weighted indicators are the most commonly used for summarizing sound exposure. However, this previous study did not measure sounds by frequency bands, in contrast to the present work. Thus, the present use of both A- and C-weighted indicators as well as CA, and low-, medium-, and high-frequency noise indicators allowed for a more comprehensive examination of the relationship between specific frequencies of sound and resulting stress levels, although it led to a negative finding.

Compared to most previous studies which focused on individuals' chronic exposures to specific sources of noise at static locations (1), the present study considers individuals' personal exposures to different sources of noise at multiple geographic locations and during travel between these locations. The main strength of this study lies in the particular GPS-based mobility survey methodology which enabled the identification of transportation modes and start and end times of trip stages. This detailed information was used in conjunction with the time-stamped noise data. A related strength lies in the large number of observations collected which translated to 7800 trip stages. This is considerably more than previous studies looking at personal noise exposure and stress. Our GPS-based mobility survey also allowed us to innovatively collect information on stress during trips at the trip stage level. Overall, the use of wearable sensors and innovative survey methodologies for trip conditions allowed for the accurate and continuous measurement of personal exposure over time as well as its effects on stress. This enabled the investigation of the noise – stress association in a "real-life" context while moving away from previously-used laboratory environments.

Regarding limitations, although participants were instructed to wear the noise dosimeters over 4 full days with the exception of sleep, dosimeter data contain missing periods. An additional challenge lies in the fact that we had to align two separately collected sources of data for the same trips (GPS / mobility survey data and noise data). This was addressed through the use of timestamps indicating the start and end points of each trip, as well as points of change when it came to modes of transportation. Although the start and end times of trip stages were derived from an algorithmic processing of GPS data and were confirmed during the phone mobility survey with the participants, challenges to this approach lie in the fact that the accuracy of the starts and ends of trips as well as the changes in mode of transportation during trips can be reduced for a number of reasons. For example, accuracy is reduced when GPS data is lacking and approximated timestamps must be assigned manually during the mobility survey. Furthermore, "transfers" between trip stages can occur in an underground environment in the Paris region, especially for public transportation. As a result, geolocation data is often not available for these transfer episodes, although they do have associated start and end times. Also, certain modes of transportation (i.e., tram) consisted of a small number of measurements (only 91 out of 7800 trip stages), which made the corresponding associations less reliable than others.

Regarding noise, due to the considerable amount of data collected, automated processes were required for the filtering of data. These processing steps leading up to the calculation of the noise parameters could potentially be a source of measurement bias. It was also noted that 100 trip stages out of 7800 (1.3%) had an average LAeq below 30 dB(A), which might involve measurement error, as these levels are abnormally low.

In addition, most previously conducted studies use self-reported recall questionnaires and retrospective assessments to examine participants' stress (28,29). Similarly, our study assessed stress in trips *a posteriori* during the mobility survey, with a delay between the end of data collection and the survey. Although attempts were made to perform the mobility survey with as minimal of a delay as possible, this approach is susceptible to bias as psychological stress is highly dynamic and *a posteriori* reinterpretation is possible. Therefore, we cannot exclude measurement error and recall bias related to specific participants or specific trips. These issues indicate the need for an integrated assessment approach which incorporates ecological momentary assessment (EMA), i.e., in situ surveys of stress using smartphones, with GPS receivers and wearable noise sensors to produce accurate assessments of short-term effects of noise on stress (30).

An additional limitation is whether the study participants are representative of a larger population. Originally, a sample of around 49000 individuals were selected from the census as being eligible for participation in the study. Participants' interest in engaging in the study was gauged through postal mail. Therefore, although the final group of participants was not a convenience sample, it is also not a "representative sample" given the small final sample size.

However, individual and contextual determinants of participation in the study have been investigated, and it should allow us to address potential selection biases.

Another limitation is related to the fact that this study mainly focuses on the relationship between measured noise over the short term and acute rather than chronic psychological stress. It is important to note, however, that the impacts of noise on individuals' psychological stress may stem from a cumulative exposure over time and may only become apparent after a certain period (time-lagged and accumulated effect). The long-term portion of the Mobilisense study will compare participants' health outcomes after a one or two-year follow-up period, permitting for the investigation of the relationship on a longer temporal scale.

Conclusion

Our future research will evaluate the interactions between mobility contexts and sound levels in their association with psychological stress. Furthermore, our future work will have to take into account the subjectivity of noise perception which can be affected by non-acoustic factors like the personal sensitivity to noise, levels of mental arousal, the meaning of and the predictability of sound levels, as well as perceived control over the sound source. Moreover, future studies should give more consideration to the behavioural consequences of noise, for example in terms of physical activity, as research suggests noise affects whether people choose to exercise or not (31). Some of these aspects could be incorporated into future research through the use of an enhanced version of the mobility survey. Future work should also take into account potentially unmeasured confounders which may also affect stress, such as air pollution, vibration, etc. as studies have shown that it is difficult to separate these effects from those of noise (31). These stressors can be accounted for through the use of additional sensors such as the air pollution monitors that were used in the MobiliSense study.

The combination of GPS and noise dosimeter data collection along with the use of a GPS-based mobility survey allowed us to better explore the relationship between noise exposure and stress at an unprecedented level of accuracy: at the level of trip stages for which exact transportation modes were identified. The associations that were found between noise indicators and subjectively reported stress indicated that overall noise levels rather than particular noise frequencies contributed to stress. Although perhaps only applicable to cities with a similar urban and transport infrastructure, our results suggest that noise exposure varies depending on the modes of transportation taken. We are also able to conclude that noise at levels typically encountered in transport poses a threat to human wellbeing by increasing stress. These findings suggest that noise is an important concern in the daily lives of urban residents which urgently needs to be addressed through engineering and adequate urban planning transformations related to transportation systems.

References

1. Basner M, Babisch W, Davis A, Brink M, Clark C, Janssen S, et al. Auditory and non-auditory effects of noise on health. The Lancet. 2014 Apr 12;383(9925):1325–32.
2. Ising H, Kruppa B. Health effects caused by noise : Evidence in the literature from the past 25 years. Noise Health. 2004 Jan 1;6(22):5.
3. Lusk SL, Gillespie B, Hagerty BM, Ziemba RA. Acute Effects of Noise on Blood Pressure and Heart Rate. Arch Environ Health Int J. 2004 Aug 1;59(8):392–9.
4. Sørensen Mette, Andersen Zorana J., Nordsborg Rikke B., Becker Thomas, Tjønneland Anne, Overvad Kim, et al. Long-Term Exposure to Road Traffic Noise and Incident Diabetes: A Cohort Study. Environ Health Perspect. 2013 Feb 1;121(2):217–22.
5. Dzhambov A, Dimitrova DD. Self-reported occupational noise may be associated with prevalent chronic obstructive pulmonary disease in the us general population Dzhambov AM, Dimitrova DD - Noise Health [Internet]. 2017 [cited 2020 Feb 11]. Available from: http://www.noiseandhealth.org/article.asp?issn=1463-1741;year=2017;volume=19;issue=88;spage=115;epage=124;aulast=Dzhambov
6. Matthews SA. The Salience of Neighborhood: Some Lessons from Sociology. Am J Prev Med. 2008 Mar 1;34(3):257–9.
7. Bild E, Pfeffer K, Coler M, Rubin O, Bertolini L. Public Space Users' Soundscape Evaluations in Relation to Their Activities. An Amsterdam-Based Study. Front Psychol [Internet]. 2018 [cited 2020 Feb 6];9. Available from: https://www.frontiersin.org/articles/10.3389/fpsyg.2018.01593/full
8. Stansfeld S, Haines M, Brown B. Noise and Health in the Urban Environment. Rev Environ Health [Internet]. 2000 Jan [cited 2020 Feb 11];15(1–2). Available from:

https://www.degruyter.com/view/j/reveh.2000.15.1-2/reveh.2000.15.1-2.43/reveh.2000.15.1-2.43.xml

9. Levy-Leboyer C, Naturel V. Neighbourhood noise annoyance. J Environ Psychol. 1991 Mar;11(1):75–86.

10. Seidler A, Wagner M, Schubert M, Droge P, Romer K, Pons-Kuhnemann J, et al. Aircraft, road and railway traffic noise as risk factors for heart failure and hypertensive heart disease-A case-control study based on secondary d... - PubMed - NCBI [Internet]. 2016 [cited 2020 Feb 10]. Available from: https://www.ncbi.nlm.nih.gov/pubmed/27667192/

11. Willich SN, Wegscheider K, Stallmann M, Keil T. Noise burden and the risk of myocardial infarction. Eur Heart J. 2006 Feb 1;27(3):276–82.

12. Selander J, Nilsson ME, Bluhm G, Rosenlund M, Lindqvist M, Nise G, et al. Long-Term Exposure to Road Traffic Noise and Myocardial Infarction. Epidemiology. 2009;20(2):272–9.

13. Kwan M-P. From place-based to people-based exposure measures. Soc Sci Med. 2009 Nov 1;69(9):1311–3.

14. Kwan M-P, Peterson RD, Browning CR, Burrington LA, Calder CA, Krivo LJ. Reconceptualizing Sociogeographic Context for the Study of Drug Use, Abuse, and Addiction. In: Thomas YF, Richardson D, Cheung I, editors. Geography and Drug Addiction [Internet]. Dordrecht: Springer Netherlands; 2008 [cited 2020 Feb 13]. p. 437–46. Available from: https://doi.org/10.1007/978-1-4020-8509-3_26

15. Yu X, Ivey C, Huang Z, Gurram S, Sivaraman V, Shen H, et al. Quantifying the impact of daily mobility on errors in air pollution exposure estimation using mobile phone location data. Environ Int. 2020 Aug 1;141:105772.

16. Jiang L, Nellthorp J. Valuing transport noise impacts in public urban spaces in the UK: Gaps, opportunities and challenges. Appl Acoust. 2020 Sep;166:107376.

17. Perchoux C, Chaix B, Cummins S, Kestens Y. Conceptualization and measurement of environmental exposure in epidemiology: Accounting for activity space related to daily mobility. Health Place. 2013 May 1;21:86–93.

18. Rainham D, McDowell I, Krewski D, Sawada M. Conceptualizing the healthscape: Contributions of time geography, location technologies and spatial ecology to place and health research. Soc Sci Med. 2010 Mar 1;70(5):668–76.

19. Srivastava G, Schönfelder S. On the temporal variation of human activity spaces. 2003;42.

20. SVANTEK. SV104 Noise Dosimeter [Internet]. [cited 2020 Oct 19]. Available from: http://svantek.com/lang-en/product/4/sv_104_noise_dosimeter.html#specification

21. Pulsar Instruments. Understanding A-C-Z noise frequency weightings | Environmental XPRT [Internet]. [cited 2021 Feb 25]. Available from: https://www.environmental-expert.com/articles/understanding-a-c-z-noise-frequency-weightings-799829

22. Wereski M. The Threshold of Hearing. STEAM. 2015 Sep 4;2(1):1–4.

23. Hensher DA, Button KJ, editors. Handbook of Transport Modelling: 2nd Edition [Internet]. Emerald Group Publishing Limited; 2007 [cited 2020 Mar 25]. (Handbooks in Transport; vol. 1). Available from: http://www.emeraldinsight.com/doi/book/10.1108/9780857245670

24. RStudio Team. RStudio | Open source & professional software for data science teams [Internet]. [cited 2020 Jun 11]. Available from: https://rstudio.com/

25. Kincaid CD. 198-30: Guidelines for Selecting the Covariance Structure in Mixed Model Analysis. :8.

26. Pinheiro JC, Bates DM, editors. Theory and Computational Methods for Linear Mixed-Effects Models. In: Mixed-Effects Models in S and S-PLUS [Internet]. New York, NY: Springer; 2000 [cited 2020 Apr 2]. p. 57–96. (Statistics and Computing). Available from: https://doi.org/10.1007/0-387-22747-4_2

27. Aarbaoui TE, 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. 2020 Mar;30(2):383–93.

28. Douglas O, Murphy E. Source-based subjective responses to sleep disturbance from transportation noise. Environ Int. 2016 Jul 1;92–93:450–6.

29. Evans GW, Lercher P, Meis M, Ising H, Kofler WW. Community noise exposure and stress in children. J Acoust Soc Am. 2001 Mar;109(3):1023–7.

30. Schwartz JE, Stone AA. Strategies for analyzing ecological momentary assessment data. Health Psychol Off J Div Health Psychol Am Psychol Assoc. 1998 Jan;17(1):6–16.

31. Sorensen M, Munzel T, Brink M, Roswall N, Wunderli JM, Foraster M. Transport, noise, and health | DORA Empa [Internet]. [cited 2021 Dec 13]. Available from: https://www.dora.lib4ri.ch/empa/islandora/object/empa%3A21872

Figure 1: Flow chart showing study stages and the data collected from each stage

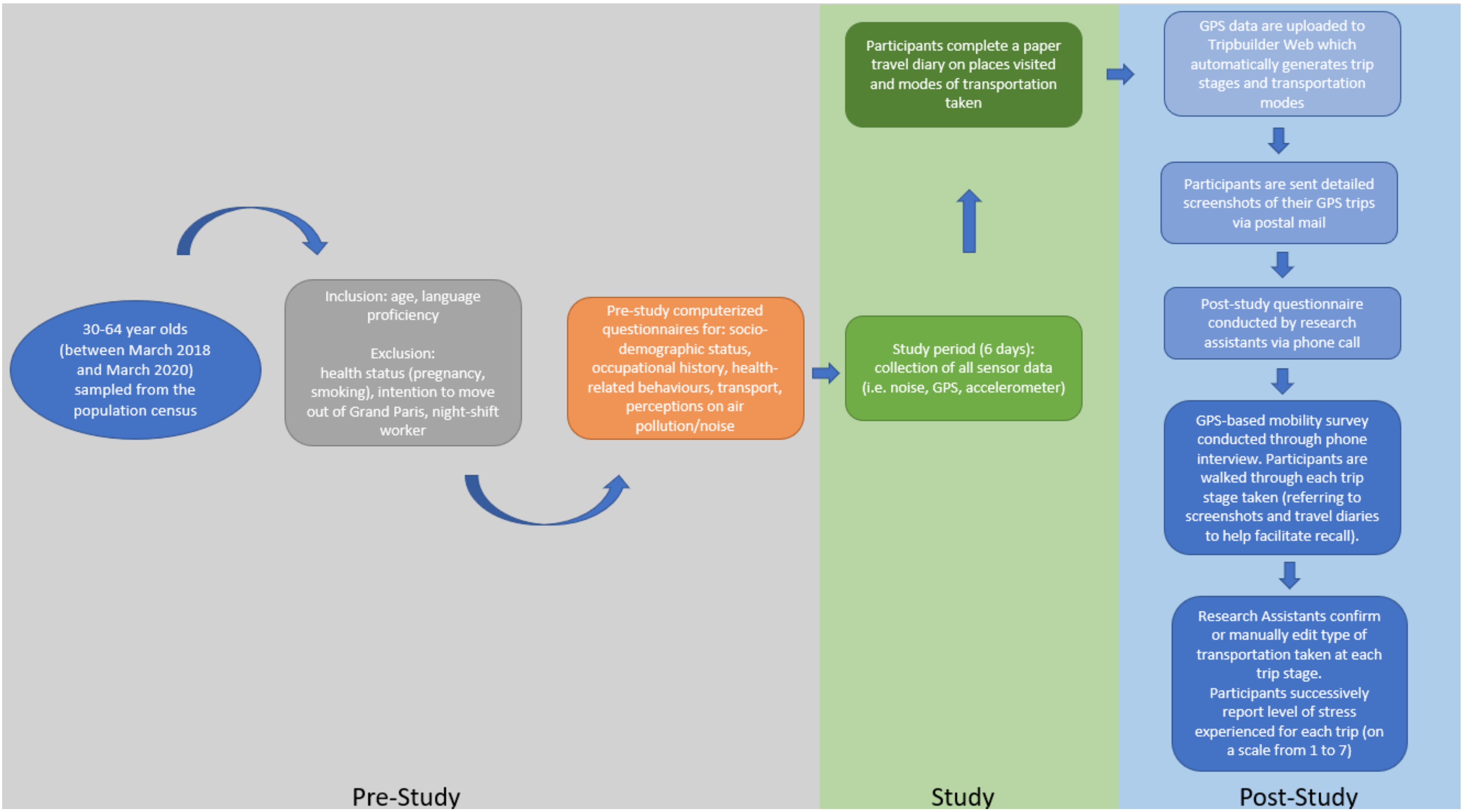

Figure 2: Distribution of LAeqT by Transportation Mode

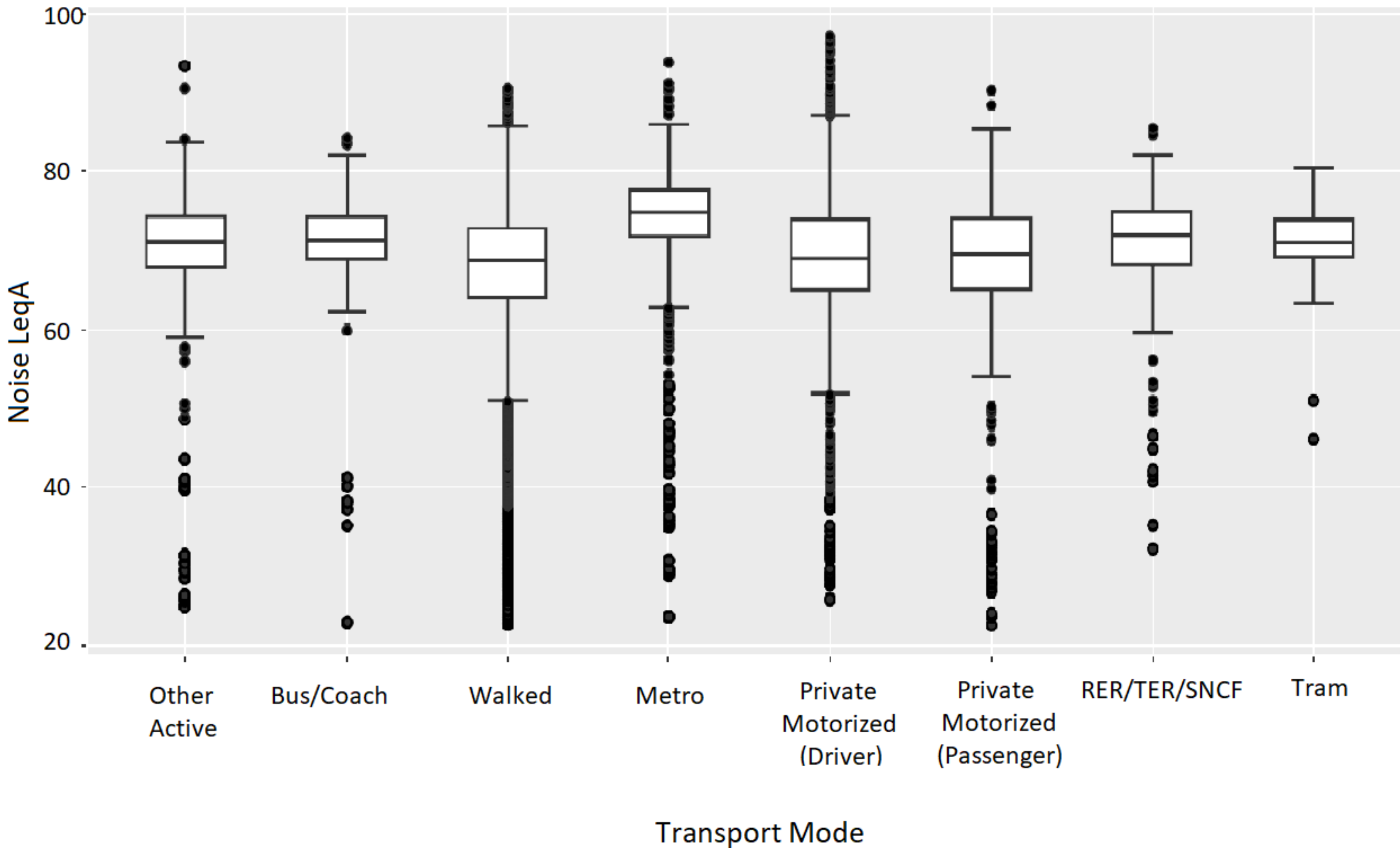

Figure 3: Correlation Matrix of Noise Indicators

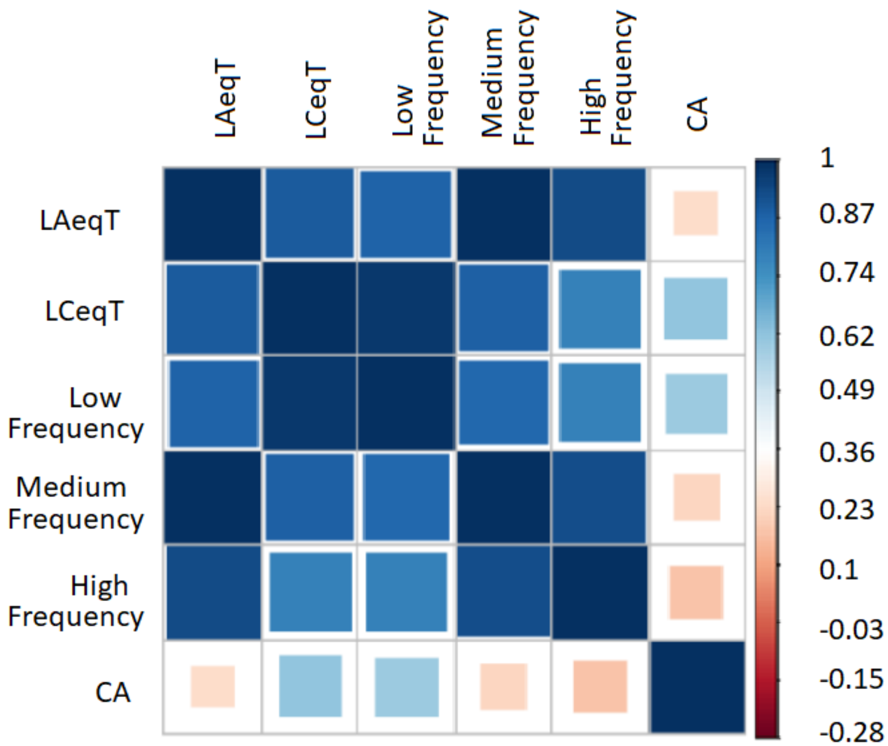

Table 1: Associations between mode of transportation and indicators of noise exposures from random effect linear models controlling for time autocorrelation and sociodemographic variables, the Mobilisense Study

	LAeqT	LCeqT	CA	Low Freq	Medium Freq	High Freq
Transportation mode						
Walking	Ref.	Ref.		Ref.	Ref.	Ref.
Other active	3.514 (2.411, 4.617)	4.921 (3.816, 6.026)	1.399 (0.815, 1.983)	5.718 (4.572, 6.865)	3.475 (2.324, 4.625)	3.606 (2.598, 4.613)
Bus/Coach	2.728 (1.433, 4.022)	10.360 (9.063, 11.658)	7.655 (6.955, 8.355)	8.690 (7.345, 10.035)	2.574 (1.224, 3.923)	2.188 (1.005, 3.371)
Metro	5.475 (4.695, 6.256)	6.079 (5.296, 6.862)	0.580 (0.158, 1.002)	5.973 (5.161, 6.784)	5.661 (4.847, 6.476)	4.055 (3.341, 4.768)
RER/TER/SNCF	4.033 (2.989, 5.077)	5.083 (4.037, 6.129)	1.046 (0.482, 1.610)	5.494 (4.409, 6.578)	4.308 (3.219, 5.397)	1.407 (0.453, 2.361)
Tram	2.307 (0.414, 4.199)	5.264 (3.367, 7.160)	2.914 (1.891, 3.938)	5.393 (3.426, 7.359)	2.513 (0.539, 4.486)	-1.810 (-3.539, -0.080)
Personal motorized (driver)	2.201 (1.576, 2.826)	10.491 (9.865, 11.117)	8.360 (8.026, 8.693)	9.576 (8.927, 10.226)	1.786 (1.135, 2.438)	-0.577 (-1.148, -0.007)
Personal motorized (passenger)	-0.300 (-1.469, 0.869)	7.049 (5.877, 8.220)	7.333 (6.703, 7.964)	6.407 (5.193, 7.622)	-0.745 (-1.964, 0.474)	-3.254 (-4.322, -2.185)
Education level						
Primary, lower secondary	Ref.	Ref.		Ref.	Ref.	Ref.
Higher secondary	-3.805 (-7.666, 0.056)	-2.421 (-6.255, 1.413)	1.398 (0.007, 2.789)	-2.615 (-6.666, 1.437)	-4.100 (-8.137, -0.062)	-4.354 (-7.812, -0.895)
Intermediate tertiary	-4.693 (-8.662, 0.723)	-4.268 (-8.209, -0.326)	0.457 (-0.972, 1.886)	-4.353 (-8.518, -0.188)	-4.999 (-9.150, -0.849)	-4.736 (-8.292, -1.181)
Upper tertiary	-2.084 (-5.902, 1.734)	-1.629 (-5.421, 2.162)	0.466 (-0.908, 1.840)	-1.550 (-5.556, 2.457)	-2.297 (-6.289, 1.695)	-2.306 (-5.726, 1.114)
Employment						
Unstable job	Ref.	Ref.		Ref.	Ref.	Ref.
Stable job	-0.595 (-4.769, 3.580)	-0.778 (-4.921, 3.365)	-0.201 (-1.676, 1.275)	-1.252 (-5.633, 3.129)	-0.539 (-4.903, 3.826)	-1.140 (-4.877, 2.596)
Unemployed	-0.052 (-5.987, 5.883)	-0.893 (-6.785, 4.999)	-0.894 (-3.007, 1.219)	-2.564 (-8.793, 3.666)	-0.085 (-6.291, 6.121)	-0.392 (-5.706, 4.922)
Retired	-1.739 (-6.777, 3.300)	-1.042 (-6.044, 3.960)	0.700 (-1.095, 2.494)	-1.610 (-6.898, 3.678)	-1.865 (-7.134, 3.404)	-1.930 (-6.441, 2.582)
Other	-0.198 (-5.016, 4.620)	-0.795 (-5.578, 3.987)	-0.638 (-2.349, 1.073)	-1.324 (-6.380, 3.733)	-0.160 (-5.198, 4.878)	-0.413 (-4.726, 3.900)
Relationship (couple vs. not)	-1.407 (-3.638, 0.825)	-2.129 (-4.345, 0.087)	-0.740 (-1.544, 0.063)	-1.214 (-3.556, 1.127)	-1.346 (-3.679, 0.987)	-1.034 (-3.033, 0.965)
Household income						
NA	-2.547 (-8.373, 3.279)	-1.378 (-7.165, 4.410)	1.141 (-1.024, 3.307)	-1.209 (-7.319, 4.901)	-2.474 (-8.565, 3.616)	-1.626 (-6.850, ,3.598)
1st tertile	Ref.	Ref.		Ref.	Ref.	Ref.
2nd tertile	-0.762 (-3.013, 1.489)	-1.629 (-3.864, 0.605)	-0.801 (-1.606, 0.004)	-1.255 (-3.618, 1.107)	-0.732 (-3.086, 1.621)	0.050 (-1.966, 2.065)
3rd tertile	-1.598 (-4.092, 0.896)	-0.695 (-3.288, 1.897)	-0.012 (-0.906, 0.883)	-1.254 (-3.871, 1.363)	-1.624 (-4.231, 0.984)	-1.254 (-3.487, 0.980)
Female (vs. male)	0.021 (-1.694, 1.736)	-0.048 (-1.751, 1.654)	-0.055 (-0.671, 0.560)	0.629 (-1.171, 2.429)	0.025 (-1.768, 1.818)	-0.366 (-1.902, 1.170)
Age group						
30-44	Ref.	Ref.		Ref.	Ref.	Ref.
45-60	0.469 (-1.583, 2.522)	0.509 (-1.529, 2.547)	0.073 (-0.661, 0.808)	0.580 (-1.574, 2.734)	0.472 (-1.675, 2.618)	0.599 (-1.239, 2.438)
≥60	0.386 (-2.515, 3.286)	-0.300 (-3.180, 2.580)	-0.629 (-1.669, 0.410)	-0.475 (-3.519, 2.569)	0.441 (-2.592, 3.474)	0.100 (-2.498, 2.698)
Weekend vs. weekdays	1.271 (0.656, 1.887)	0.784 (0.167, 1.401)	-0.440 (-0.768, -0.112)	1.486 (0.846, 2.126)	1.317 (0.674, 1.959)	1.282 (0.719, 1.844)
Time						
Morning	0.276 (-0.251, 0.804)	0.853 (0.324, 1.381)	0.577 (0.292, 0.862)	0.155 (-0.395, 0.705)	-1.556 (-2.406, -0.705)	0.956 (0.474, 1.438)
Day	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Evening	-0.470 (-0.962, 0.021)	-0.215 (-0.707, 0.278)	0.270 (0.004, 0.535)	-0.572 (-1.084, 0.059)	-5.500 (-6.295, -4.704)	-0.337 (-0.786, 0.112)

Table 2: Quasi-Poisson models for the relationship between noise exposure and stress, adjusted for sociodemographic variables and adjusted or not for transportation modes: ratios (95% confidence intervals)

	Adjusted for sociodemographics	Adjusted for sociodemographics and transportation modes
Weekend vs. weekdays	1.392 (1.221, 1.587)	1.349 (1.188, 1.532)
Time		
Morning	1.259 (1.254, 1.264)	1.151 (1.052, 1.260)
Day	Ref.	Ref.
Evening	1.058 (1.052, 1.064)	1.032 (0.942, 1.131)
Education Level		
Primary, lower secondary	Ref.	Ref.
Higher secondary	1.498 (0.299, 7.499)	1.289 (0.302, 5.504)
Intermediate tertiary	1.094 (0.208 5.761)	0.912 (0.204, 4.079)
Upper tertiary	2.231 (0.456, 10.924)	1.889 (0.451, 7.907)
Employment		
Unstable job	Ref.	Ref.
Stable job	1.602 (0.306, 8.397)	1.528 (0.346, 6.738)
Unemployed	0.825 (0.074, 9.185)	0.823 (0.094, 7.197)
Retired	1.286 (0.174, 9.480)	1.688 (0.280, 10.170)
Other	1.242 (0.183, 8.422)	1.319 (0.237, 7.341)
Relationship (couple vs. not)	0.769 (0.315, 1.874)	0.858 (0.384, 1.915)
Income		
NA	0.142 (0.007, 2.771)	0.133 (0.008, 2.161)
1st tertile	Ref.	Ref.
2nd tertile	0.827 (0.342, 2.001)	0.838 (0.379, 1.856)
3rd tertile	0.483 (0.182, 1.287)	0.458 (0.190, 1.107)
Age Group		
30-44	Ref.	Ref.
45-60	0.978 (0.433, 2.206)	0.921 (0.444, 1.914)
≥60	0.876 (0.272, 2.817)	0.572 (0.197, 1.659)
Female (vs. male)	0.740 (0.373, 1.470_	0.672 (0.362, 1.246)
Transportation Mode		
Walking		Ref.
Other Active		2.796 (2.338, 3.343)
Bus/Coach		1.859 (1.518, 2.277)
Metro		1.862 (1.639, 2.114)
RER/TER/SNCF		2.022 (1.724, 2.370)
Tram		0.962 (0.600, 1.544)
Personal Transport Driver		1.813 (1.617, 2.031)
Personal Transport Passenger		1.262 (1.042, 1.529)

Table 3: Associations between noise indicators and stress analyzed at the trip stage level, after adjustment for sociodemographic variables, day of week, time of day, and transportation mode from Quasi-Poisson models: null, 1-indicator, and 2-indicator models

	LAeqT u: 10 dB(A)	LCeqT u: 10 dB(A)	CA u: 1 dB(A)	Low Frequency u: 10 dB(A)	Medium Frequency u: 10 dB(A)	High Frequency u: 10 dB(A)	R^2	RMSE
Null							0.6372	2.9442
1-indicator								
LAeqT	1.118 (1.067, 1.172)						0.6402	2.9408
LCeqT		1.091 (1.041, 1.142)					0.6393	2.9314
CA			0.993 (0.985, 1.001)				0.6375	2.9477
Low frequency				1.079 (1.032, 1.128)			0.6392	2.9288
Medium frequency					1.110 (1.061, 1.161)		0.6399	2.9417
High frequency						1.097 (1.045, 1.152)	0.6396	2.9383
2-indicator								
LAeqT + LCeqT	1.132 (1.043, 1.229)	0.985 (0.908, 1.070)					0.6403	2.9423
LAeqT + CA	1.115 (1.062, 1.171)		0.999 (0.990, 1.007)				0.6403	2.9423
LAeqT + Low frequency	1.132 (1.052, 1.218)			0.985 (0.918, 1.056)			0.6402	2.9433
LAeqT + Medium frequency	1.472 (0.843, 2.570)				0.769 (0.452, 1.307)		0.6408	2.9380
LAeqT + High frequency	1.146 (1.049, 1.253)					0.970 (0.883, 1.065)	0.6400	2.9407

Supplementary Material

Table 1: Counts and percentages for the number of days of delay between the end of the study period and the mobility survey

Number of Days of Delay	Count	Percentage
0	1	0.403
1	9	3.629
2	35	14.113
3	40	16.129
4	52	20.968
5	38	15.323
6	28	11.290
7	16	6.452
8	5	2.016
9	5	2.016
10	7	2.823
11	2	0.806
12	1	0.403
14	2	0.806
15	1	0.403
16	1	0.403
22	1	0.403
23	1	0.403
28	1	0.403