



Associations between Aircraft Noise, Sleep, and Sleep–Wake Cycle: Actimetric Data from the UK Biobank Cohort near Four Major Airports

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BACKGROUND: Nighttime aircraft noise may affect people's sleep, yet large-scale evidence using objective and subjective measures remains limited.

OBJECTIVE: Our aim was to investigate associations between nighttime aircraft noise exposure and objectively measured sleep disturbance using a large UK cohort.

METHODS: We used data from 105,770 UK Biobank cohort participants exposed and unexposed to aircraft noise who lived in 44 local authority districts near 4 international airports in England. We used a generalized linear regression model to examine cross-sectional associations between aircraft noise L_{night} (23:00 hours–07:00 hours) and 7-d actimetric measures collected 2013–2015 ($n = 22,102$). We also used Logit and generalized estimating equations models to examine associations between L_{night} and self-reported sleep measures at enrollment (2006–2010) and follow-up (2012–2013). This approach allowed us to compare and contrast the results and support potential future meta-analyses on noise-related sleep disturbance.

RESULTS: Cross-sectional analyses of actimetric data suggested sleep disturbance associated with L_{night} , showing higher level of movements during the least active continuous 8-h time period [β : 0.12 milligravitational units; 95% confidence interval (CI): 0.013, 0.23]. We also saw disrupted sleep–wake cycles as indicated by index scores of lower relative amplitude (β : –0.006; 95% CI: –0.007, –0.005), poorer interdaily stability (β : –0.010; 95% CI: –0.014, –0.006), and greater intradaily variability (β : 0.021; 95% CI: 0.019, 0.023), comparing $L_{\text{night}} \geq 55$ dB with <45 dB. Repeated cross-sectional analyses found a 52% higher odds of more frequent daytime dozing [odds ratio (OR) = 1.52; 95% CI: 1.32, 1.75] for $L_{\text{night}} \geq 55$ dB in comparison with <45 dB, whereas the likelihood for more frequent sleeplessness was more uncertain (OR = 1.13; 95% CI: 0.92, 1.39). Higher effect sizes were seen in preidentified vulnerable groups, including individuals >65 y of age and those with diabetes or dementia.

CONCLUSION: Individuals exposed to higher levels of aircraft noise experienced objectively higher levels of sleep disturbance and changes in sleep–wake cycle. <https://doi.org/10.1289/EHP14156>

Introduction

The World Health Organization (WHO) Environmental Noise Guidelines for the European Region published in 2018 recommended reducing the noise levels produced by aircraft during nighttime to below 40 dB L_{night} [A-weighted equivalent noise level (L_{eq}) over the 8-h night period of 23:00 hours–07:00 hours] because nighttime aircraft noise above this level is associated with adverse effects on sleep.¹ In the United Kingdom alone, nearly 1 million people ($\sim 1.5\%$ of the UK population) were affected by aircraft noise greater than $L_{\text{night}} 55$ dB, according to the most recently published government noise action plan in 2017.²

Aircraft noise at night can disrupt sleep by evoking physiological signals in the auditory system, because the sleeping body continues to react to environmental stimuli.³ This disruption potentially results in shortened sleep, sleep awakenings, stage modifications, and autonomic responses.⁴ The 2018 WHO Environmental Noise Guidelines for the European Region used self-reported percentage of the population to be highly sleep-disturbed (%HSD) as the outcome for sleep disturbance.¹ Highly sleep-disturbed people were typically those who chose scale points close to the top of the scale (worst sleep quality) on the sleep quality questionnaires.^{5,6} The guidelines synthesized the findings of three studies that used nonnoise specified questionnaires and identified a 17% [odds ratio (OR) = 1.17; 95% confidence interval (CI): 0.54, 2.53] higher odds of self-reported high sleep disturbance for every 10 dB increase in nighttime aircraft noise.⁷ Nonnoise-specified questionnaires refer to those in which participants were asked how often they had disturbed sleep, without specifically mentioning any cause of disturbance such as noise. An update to this review using the same nonnoise-specific questionnaire approach found the odds of experiencing sleep disturbance because of aircraft noise higher by 52% (OR = 1.52; 95% CI: 1.20, 1.93; based on eight studies) per 10-dB increase in the average nighttime outdoor noise, based on eight studies.⁸

Sleep, being an unconscious process, means that self-reported sleep disturbance may be subject to recall bias.⁸ However, evidence from large-scale studies using more objective methods to evaluate sleep disturbances has been limited to date. Polysomnography (PSG), although considered the gold standard in sleep research,⁷ is relatively inconvenient and labor-intensive. The 2018 literature

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Supplemental Material is available online (<https://doi.org/10.1289/EHP14156>).

All authors declare they have no conflicts of interest related to this work to disclose.

Conclusions and opinions are those of the individual authors and do not necessarily reflect the policies or views of EHP Publishing or the National Institute of Environmental Health Sciences.

Received 13 October 2023; Revised 20 August 2024; Accepted 22 August 2024; Published 25 September 2024.

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review for the WHO Environmental Noise Guidelines identified only four studies using PSG. One study, which was rated as moderate quality, found an association between aircraft noise and polysomnography-measured probability of additional awakenings, with an OR of 1.35 (95% CI: 1.22, 1.50) per 10 dB increase in indoor LAS, max.^{7,9} However, it was not possible to estimate a pooled effect due to design variability and small sample sizes.⁷ Actimetry, a less inconvenient and labor-intensive but still relatively objective method involving wrist-worn devices to track sleep–wake cycles, has been widely used and validated.¹⁰ Most published studies using actimetric measures have relatively small sample sizes. In a study in Switzerland, 105 subjects with actimetric data were included,¹¹ and in France, 112 participants with actimetric data were involved.¹² There has still been very limited large-scale evidence on aircraft noise and sleep studies using actimetric measures, which was an important motivation for this study.

The objective of our study was to investigate the association between nighttime aircraft noise exposure and actigraphy-generated sleep disturbance outcomes. We also included self-reported sleep outcomes, as the inclusion of both objective and subjective measures to study the association between aircraft noise and sleep disturbance in the same cohort may help better understand the strengths and limitations of actimetric measures and support potential future meta-analyses on noise-related sleep disturbance. We focused on a subset of ~100,000 individuals living near four major airports, obtained from the UK Biobank, a large, broadly population-based, biomedical cohort study database. Our study serves both a hypothesis-testing study to examine the association between nighttime aircraft noise exposure and sleep disturbance as well as a hypothesis-generating one to explore potential actimetric outcomes that could act as proxies for sleep disturbance in noise studies.

Methods

Study Population

Our study analyzed data from participants in the UK Biobank cohort study, which has collected comprehensive health, lifestyle, and genetic information from 502,413 volunteer participants 40–69 y of age at recruitment between 2006 and 2010. A subset of 105,770 participants from UK Biobank were included in our study, all of whom resided in one of the 44 Local Authority Districts (LADs; as per the boundary May 2020), wholly or partially encompassed within Civil Aviation Authority (CAA) L_{den} (Day–evening–night noise level) noise contours of four major international airports [London Heathrow (LHR), London Gatwick (LGW), Birmingham (BHX), and Manchester (MAN)] in England. The participants who lived inside the noise contours within the 44 LADs are in the exposed group, whereas those living outside contour but still within the 44 LADs are comparators. The CAA L_{den} and L_{night} noise contours and 44 Local Authority Districts are presented in Figure 1.

UK Biobank has conducted baseline and multiple follow-up assessment visits. The baseline assessment (instance 0; 2006–2010) includes extensive data collected at the time of recruitment, such as information on demographics, lifestyle factors, medical history, physical measurements, and biological samples, etc. The first follow-up visit (instance 1) was conducted in the period 2012–2013. During that period, a total of 103,514 participants were invited to participate, and of those, 20,345 participants attended further assessments.¹³ For our study, we used instance 0 (2006–2010) and follow-up instance 1 (2012–2013) data.

UK Biobank has ethical approval to function as a Research Tissue Bank (RTB) from the North West Multi-Centre Research Ethics Committee (MREC) under the current REC approval number (2021, 5-y cycle): 21/NW/0157. Approval for this specific

research project application was covered by UK Biobank project approval number 59129. Under RTB approval, our study does not require separate ethical clearance.¹⁴

Outcomes

Because sleep disturbance has multiple aspects, we adopted an approach using multiple actimetric measures, some of which are novel. We additionally used self-reported measures to compare and contrast their results with those obtained from objective measures and to aid future meta-analyses that rely on self-reported data. Table S1 provides detailed definitions, data descriptions, and interpretations for each actimetric outcome, along with the questions, response options, and categorizations for each self-reported outcome.

Actimetric measures. Our actimetric measures include accelerometer derived average movements during the least active periods, time spent on sleep or in bed, and a relatively overlooked sleep aspect: the sleep–wake cycle.

A total of 236,519 participants from the UK Biobank were invited to measure their physical activity using the Axivity AX3 wrist-worn triaxial accelerometer between 1 June 2013 and 23 December 2015.¹⁵ Of those invited, 106,053 participants agreed to wear the monitor, resulting in a response rate of 44.8%.¹⁵ Among the participants who wore the monitor, 103,712 had complete actimetric data, with a median wear-time of 6.9 d (interquartile range: 6.5–7.0 d). For each participant, accelerometer data (5-s epoch time series) were extracted from UK Biobank¹⁵ and converted to R-format for processing and analysis with GGIR (version 1.11-0; <http://cran.r-project.org>).¹⁶ Participants were excluded if they failed calibration, had fewer than 3 d of valid wear (defined as >16 h per day), or wear-data were not present for each 15 min period of the 24-h cycle. Valid physical activity data [valid days, 5.8 ± 0.6 (mean \pm SD)] were obtained from 96,600 participants (93.3%),¹⁵ of whom 22,101 (for the proportion of time spent on sleep or in bed within 7 d) and 22,102 (for other actimetric measures) participants were living in any of the 44 LADs included in this study. These valid physical activity data were then previously processed to derive outcomes used in this study.

The first outcome is average acceleration during the least active 8-h period, measured in milligravitational units (mg), which provides an indication of overall activity during the rest period.¹⁷ This outcome may be used as a proxy for participant movement or arousal during their least active rest windows of time.^{18,19} The 8-h period (average from 23:06 to 07:06 in our data) was chosen because it aligns well with the 8-h window (23:00 hours to 07:00 hours) used in the L_{night} noise exposure metric we used in our study.

We used the overall average proportion of time spent on sleep or in bed (defined as nonwaking time²⁰) during the monitoring 7 d, which was previously derived using a published machine-learning methodology.²⁰ We name this outcome as time spent on sleep or in bed to aid interpretation.

We also looked at three previously derived outcomes related to a participant's sleep–wake cycle: relative amplitude (RA), intradaily variability (IV), and interdaily stability (IS).²¹ RA measures the contrast in activity levels between the most active 10 h and the least active 5 h within a 24-h period. IV measures the fragmentation of the 24-h rest–activity rhythm, whereas IS measures the stability of the rest–activity rhythm.

All actimetric outcomes were measured at one time point (in 2013–2015). Baseline UK Biobank covariate data were used in the models of actimetric measures for the 22,102 participants.

Self-reported measures. The first self-reported outcome was related to sleeplessness/insomnia and was obtained through responses to the question, “Do you have trouble falling asleep at night or do you wake up in the middle of the night?” The second

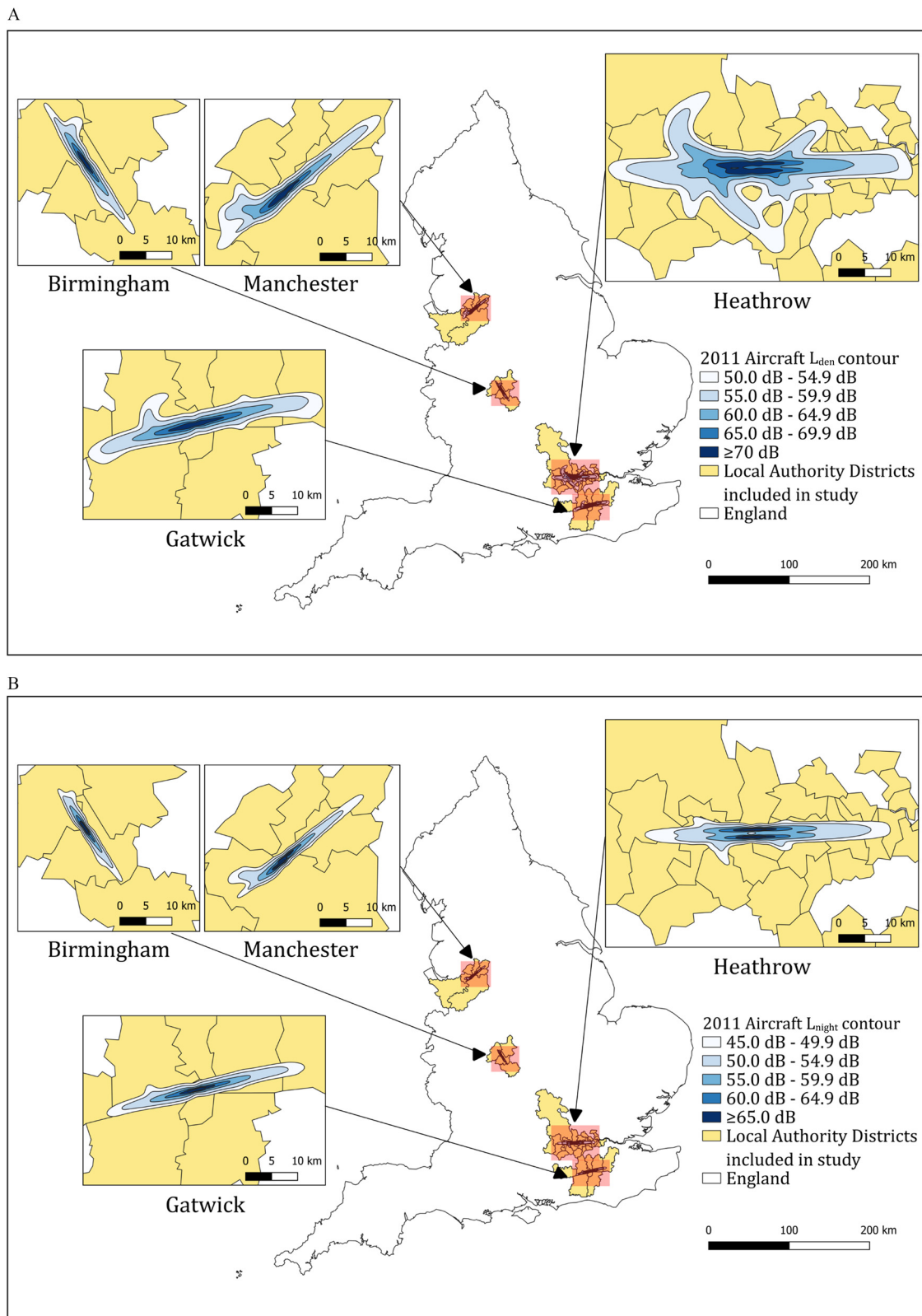


Figure 1. Maps of England showing Civil Aviation Authority noise contours for the four airports and the 44 local authorities included in the study. (A) L_{den} noise contour. (B) L_{night} noise contour. Note: L_{den} represents the day–evening–night noise level, and L_{night} refers to the A-weighted equivalent noise level (L_{eq}) measured in decibels (dB) over the 8-h night period from 23:00 hours to 07:00 hours. The Local Authority District shapefile was obtained as open-source data from <https://geoportal.statistics.gov.uk/>. The package used to create Figures 1A and 1B was QGIS.

outcome was daytime dozing/sleeping, which we obtained through responses to the question “How likely are you to doze off or fall asleep during the daytime when you don’t mean to? (e.g., when working, reading or driving)?” Last, we extracted sleep duration as the final self-reported outcome, which was obtained through responses to the question, “About how many hours sleep do you get in every 24 h? (please include naps).” These questions were measured at baseline (instance 0) and had a repeated measurement (instance 1). Any responses indicating “prefer not to say” or “do not know” were treated as missing data and excluded from the regression.

To facilitate analysis, interpretation, and to ensure comparability with other studies on the same topic, we grouped responses for self-reported sleeplessness and daytime dozing. Both questions have verbal answers with various frequencies. For example, sleeplessness has response options: “never/rarely,” “sometimes,” and “usually,” whereas response options for daytime dozing include “never/rarely,” “sometimes,” “often,” and “all of the time.” We selected the two responses indicating the highest frequency for each question; i.e., “sometimes” and “usually” were chosen as the exposure group for sleeplessness, whereas “often” and “all of the time” were selected to represent the exposure group for daytime dozing.

Aircraft Noise Exposure

The Civil Aviation Authority (CAA) provided aircraft noise surfaces (measured in L_{den} and L_{night}) for four airports—LHR, LGW, BHX, and MAN—for 2006 and for 2011. The noise contours are shown in Figure 1. These contours were modeled using ANCON version 2, taking into account variables such as height, speed profile, takeoff/landing weights, and aircraft performance data.²² Noise levels modeled by using the ANCON model have shown significant similarities with US Federal Aviation Administration’s Integrated Noise Model (INM) and have been validated by comparing sound exposure level noise calculations at grid points with noise measurements made at equivalent distances from the airport.²³ For instance, the largest variation from predicted levels, when compared with measured levels for a Boeing 747-400, was just over 2 dB.²³

Our study focused on nighttime noise, using the L_{night} metric, which is the A-weighted equivalent noise level (L_{eq}) over the 8-h night period of 23:00 hours–07:00 hours. The CAA provided data truncated to a lower level of 45 dB; levels below this specific noise exposure level are not provided.

We determined each participant’s residential noise levels by overlaying postcode centroid points onto the CAA’s L_{night} noise contours. We divided the nighttime aircraft noise exposure of the participants into four categories based on a 5-dB increment: <45 dB, ≥ 45 to <50 dB, ≥ 50 to <55 dB, and ≥ 55 dB. The 5-dB difference was chosen because a minimal 3–5 dB difference may be needed for people to detect a change in noise level.²⁴ Approximately 5% of people in the sample were exposed to noise above 50 dB.

Covariates

The covariates used were selected based on a directed acyclic graph (DAG), as depicted in Figure S1. The DAG graph was plotted based on reviews of the mechanisms of the health impacts of noise exposure^{1,25} and other related studies.^{12,26,27}

The demographic variables in this study consist of sex (male or female), age in 2006 (the time point of the first nighttime aircraft noise exposure measurement) and 2011 (the time point of the second nighttime aircraft noise exposure measurement), as well as body mass index (BMI) (continuous). We controlled for

self-reported ethnicity (White, Mixed, Asian or Asian British, Black or Black British, Chinese or others). Ethnicity may be associated with important aspects of disadvantage, including employment and earnings disparities,²⁸ as well as experiences of racism and discrimination in the United Kingdom.²⁹ The categories of ethnicity used in our study followed those of the UK Biobank dataset.³⁰

The Hedonic price model suggests an inverse association between noise exposure and house prices,^{31–33} implying a link between aircraft noise exposure and deprivation. We therefore controlled for socioeconomic factors. These include self-reported average yearly household income before tax (<£18,000, £18,000–£30,999, £31,000–51,999, £52,000–£100,000, or >£100,000), and calculated Townsend deprivation index (continuous) at the output area (a small census area) in which participants’ postcode was located at recruitment. Townsend index is an area-based score of social deprivation (accounting for unemployment, overcrowding, noncar ownership, and nonhome ownership).³⁴

Self-reported mental health or lifestyle factors include “ever seen a psychiatrist or doctor (GP) for nerves, anxiety, tension, or depression” (yes or no), smoking status (never, previous or current), and alcohol consumption (daily or almost daily, 3–4 times a week, 1–2 times a week, 1–3 times a month, special occasions only or never). We also incorporated the total number of vigorous or moderate physical activities (in days) reported by each participant per week. In cases where a participant engaged in both vigorous and moderate activities on a single day, we counted that day as 1.

Environmental covariates included modeled nighttime road traffic noise (<45 dB, ≥ 45 to <50 dB, ≥ 50 to <55 dB, and ≥ 55 dB), nighttime rail traffic noise (<45 dB, ≥ 45 to <50 dB, ≥ 50 to <55 dB, and ≥ 55 dB), average annual nitrogen dioxide (NO_2) concentration (continuous), average annual particulate matter with aerodynamic diameter <2.5 μm ($PM_{2.5}$) concentration (continuous) and greenspace percentage within a buffer of 1,000 m (continuous). Nighttime road noise at participants’ home postcodes was calculated using the CNOSSOS-EU framework using 2013 data such as traffic counts, speeds, surface roughness, building heights, wind profiles, and temperatures.^{35,36} Rail noise levels were extracted from 2011 noise maps created by Extrium on behalf of the Department for Environment, Food and Rural Affairs (DEFRA).³⁷ NO_2 concentrations for 2009 were modeled using UK-specific Land Use Regression (LUR) model.³⁸ $PM_{2.5}$ concentrations were modeled using LUR for the European Study of Cohorts for Air Pollution Effects (ESCAPE).³⁹ We used the percentage of greenspace within a 1,000-m radius of each participant calculated by Wheeler et al.⁴⁰

We additionally used the number of years a participant had lived at current address (continuous).

Field IDs or return IDs of all variables used in our study and their description can be found in Table S2.

Statistical Analysis

Descriptive statistics were used to provide a summary of the sleep outcomes, environmental variables, and covariates.

For actimetric data that only had one measurement, we used a cross-sectional design with baseline instance and 2011 aircraft noise data. We employed generalized linear regression models with a gamma distribution and identity link to investigate the association of noise exposure with actimetric sleep measures, accounting for all covariates. A gamma distribution was chosen due to its suitability for modeling positive values, whereas the identity link function was used so that the coefficient can be interpreted as the incremental change in the outcome per noise category in comparison with the reference group (<45 dB).

We employed a repeated cross-sectional design to examine the association between nighttime aircraft noise and self-reported sleep outcomes using instance 0 (2006–2010) and instance 1 (2012–2013). We used 2006 aircraft noise levels with UK Biobank instance 0 and 2011 noise levels with instance 1. We used a random-effects logit model, adjusting for all covariates, to analyze the association between nighttime aircraft noise and self-reported sleeplessness and daytime dozing, considering both sleeplessness and daytime dozing as binary. We employed a generalized estimating equations (GEE) model with random effects, adjusting for all covariates, to examine the association between nighttime aircraft noise and self-reported sleep duration. Some covariates like sex, ethnicity, household income, and some environmental variables (road noise levels, rail noise levels, NO₂, PM_{2.5}, and green-space proportion) were only available at baseline and thus baseline covariate values were used for the follow-up instance.

To account for potential differences in the noise characters across four airports, we clustered variance by four airports (LHR, LGW, BHX, and MAN), except for self-reported sleep duration as the GEE model did not support cluster robust variance.

To check the robustness of our findings, we conducted multiple sensitivity analyses. We performed regression analyses while excluding subgroups of participants susceptible to misclassification with noise exposure levels. For each sensitivity analysis, we excluded one subgroup at a time. These include participants with hearing difficulty, those who have moved homes since recruitment, and those who engaged in night-shift work.

To examine for interactions, we stratified our data based on various sociodemographic factors, including sex (male or female), ethnicity (White or non-White), age (≥ 65 y), and low and high household income groups. The national median was between £29,073 and £32,000 between 2006 and 2022.⁴¹ We thus defined incomes $<£18,000$ and £18,000–£30,999 as the low household income group and categorized the remaining income levels as the high household income group. Some home/family caregivers had considerable caregiving burden,⁴² leading to experiences of stress,⁴² distress,⁴³ depressive symptoms,⁴⁴ and/or sleep disturbances.⁴⁵ We stratified our data based on participants' involvement in home/family caregiving.

The relationship between sleep and health conditions is complex. Poor sleep can be associated with higher blood pressure,⁴⁶ mental health,⁴⁷ as well as neurological conditions.⁴⁸ There is a bidirectional relationship between sleep and diabetes. Poor sleep can be linked to a higher risk of developing type 2 diabetes,⁴⁹ whereas diabetes can also negatively impact sleep quality through symptoms such as nocturia and restless legs syndrome.⁵⁰ We therefore examined associations in participants with certain health conditions known to be linked to sleep problems: diabetes (self-reported doctor-diagnosed at baseline), hypertension (based on self-reported doctor-diagnosed cases at baseline, self-reported use of medication to treat hypertension at baseline, or recorded blood pressure readings showing systolic blood pressure ≥ 140 or diastolic blood pressure ≥ 90 at baseline), high BMI (greater than median 26.64 or less than median, measured at baseline), dementia (diagnosis up to 2020 using multiple ascertainment sources), mental health issues [defined as having seen a psychiatrist or doctor (GP) for nerves, anxiety, tension, or depression at baseline], and sleep disorder (self-reported, primary care–diagnosed or hospital diagnosed up to 2023).

We employed a complete case approach to analyze the data. Any observations with missing values in any of the variables included in the regression analysis were excluded.

All statistical analyses were conducted using Stata software (version 18; STATA Corp.), and the significance level was set at $p < 0.05$.

Results

Descriptive Summary

The descriptive summary of sleep outcomes, socio-economic variables, environmental variables, mediators and moderators can be found in Table 1. We had a total of 105,770 participants, with 57,381 (54.3%) identifying as female. Ethnicity information was available for 104,739 individuals, with 91,251 (86.3%) identifying as White, 5,194 (4.9%) as Asian, and 4,386 (4.1%) as Black. Participants were recruited at ages 40–70 y when attending the baseline assessment. In 2006 the mean age of participants stood at 53.7 y [standard deviation (SD) = 8.3], spanning an age range from 35 to 72 y of age.

Descriptive analysis of sleep variables. We present a Venn diagram to show the number of participants who lived near the four airports and had valid responses to the outcomes included in our study in Figure 2. Among the 105,770 participants, 22,101 had actimetric-generated average proportions of time spent on sleep or in bed (7-d average; defined as nonwaking behavior²⁰) using the variable ID 40046 in the UK Biobank. Actimetry identified that they spent an average of 36% (SD = 5%) of their time on sleep or in bed. This is equivalent to 8 h and 38 min per day on average. A few individuals had actimetric data that passed the quality control as outlined in a previous paper²⁰ but had either a very low or very high number of hours spent sleeping or in bed according to the algorithm. These include a total of 3, 5, 6, and 17 participants who had less than a 2-h, 2–3-h, 3–4-h, or 4–5-h period asleep or in bed, respectively. In addition, one participant spent more than 18 h sleeping or in bed.

A total of 22,102 participants had actimetric variables relating to average acceleration during the least active 8-h period and sleep-wake cycle. The average acceleration was 4.5 mg (SD = 1.8). The mean relative amplitude, intradaily variability and interdaily stability were 0.88 (SD = 0.05), 0.66 (SD = 0.17), and 0.66 (SD = 0.11), respectively.

When looking at self-reported data, respondents reported an average of 7 h and 6 min ($n = 105,770$; SD = 1 h and 6 min) of sleep per day in the baseline survey and 7 h and 12 min ($n = 6,143$; SD = 1 h and 6 min) in the follow-up survey. A total of 73.6% ($n = 77,806$) in instance 0 and 77.1% ($n = 4,737$) in instance 1 reported that they “sometimes” or “usually” experienced sleeplessness. However, most respondents in both instances indicated that they “never/rarely” or “sometimes” experienced daytime dozing [95.7% ($n = 101,179$) in instance 0 and 97.4% ($n = 5,984$) in instance 1]. Almost identical results on self-reported sleeplessness, daytime dozing, and sleep duration were seen when restricted to the $\sim 20\%$ of the participants in our sample with actimetric data.

Descriptive analysis of aircraft noise variables. Nighttime aircraft noise data (L_{night}) for all four airports considered were available for 2006 and 2011. In 2006, 7,829 (7.4%), 3,841 (3.6%), and 1,733 (1.6%) participants experienced L_{night} levels of ≥ 45 to <50 dB, ≥ 50 to <55 dB, and ≥ 55 dB, respectively. By 2011, these numbers had slightly decreased to 7,383 (7.0%), 3,491 (3.3%), and 1,404 (1.3%), respectively.

Nighttime road noise levels were available for 2013 for 105,763 participants: 44,474 (42.1%) experienced nighttime road noise levels <45 dB; 38,046 (36.0%) at ≥ 45 to <50 dB; 13,434 (12.7%) at ≥ 50 to <55 dB; and 9,809 (9.3%) at ≥ 55 dB, respectively. For railway noise (available for 2011), 102,627 (97.0%) participants were exposed to levels <45 dB. A total of 1,672 (1.6%), 882 (0.8%), and 589 (0.6%) participants experienced noise levels of ≥ 45 to <50 dB, ≥ 50 to <55 dB, and ≥ 50 dB, respectively.

Table 1. Descriptive summary of UK Biobank data sleep variables, socioeconomic variables, and environmental variables used in study of airport noise and sleep [for continuous variables: mean \pm SD (min-max) (*n*, % of *N*), or for categorical variables: *n* (% of *N*)].

Variable name	Baseline (instance 0: 2006–2010) <i>N</i> = 105,770	First follow-up (instance 1: 2012–2013) <i>N</i> = 6,143
Sleep variables		
Average acceleration over least-active continuous 8 h (mg) (Baseline <i>n</i> = 22,102, 20.9%)	4.5 \pm 1.8 (1.6–39.2)	—
Proportion of time spent on sleep or in bed (7-d average) (Baseline <i>n</i> = 22,101, 20.9%)	0.36 \pm 0.05 (0.02–0.73)	—
Relative amplitude (unitless) (Baseline <i>n</i> = 22,102, 20.9%)	0.88 \pm 0.05 (0.28–0.97)	—
Intra-daily variability (unitless) (Baseline <i>n</i> = 22,102, 20.9%)	0.66 \pm 0.18 (0.22–2.04)	—
Interdaily stability (unitless) (Baseline <i>n</i> = 22,102, 20.9%)	0.66 \pm 0.11 (0.04–0.98)	—
Sleep duration [decimal time (24-h clock)] (Baseline <i>n</i> = 105,770, 20.9%; first follow-up <i>n</i> = 6,143, 100%)	07 h:06 m \pm 01 h:06 (1 h–23 h)	07 h:12 m \pm 01 h:06 (1 h–16 h)
Sleeplessness/insomnia		
Never or rarely	27,308 (25.8%)	1,403 (22.8%)
Sometimes or usually	77,806 (73.6%)	4,737 (77.1%)
Missing	656 (0.6%)	3 (0.0%)
Self-reported daytime dozing		
Never, rarely or sometimes	101,179 (95.7%)	5,984 (97.4%)
Often or all of the time	3,213 (3.0%)	145 (2.4%)
Missing	1,378 (1.3%)	14 (0.2%)
Social demographic variables		
Sex		
Female	57,381 (54.3%)	3,286 (53.5%)
Male	48,387 (45.7%)	2,857 (46.5%)
Missing	2 (0.0%)	0 (0.0%)
Ethnicity		
White	91,251 (86.3%)	5,929 (96.5%)
Mixed	1,120 (1.1%)	34 (0.6%)
Asian or Asian British	5,194 (4.9%)	56 (0.9%)
Black or Black British	4,386 (4.1%)	49 (0.8%)
Chinese	612 (0.6%)	22 (0.4%)
Other	2,176 (2.1%)	34 (0.6%)
Missing	1,031 (1.0%)	19 (0.3%)
Average household income before tax		
<£18,000	17,083 (16.2%)	1,076 (17.5%)
£18,000–£30,999	19,213 (18.2%)	1,638 (26.7%)
£31,000–£51,999	21,678 (20.5%)	1,497 (24.4%)
£52,000–£100,000	20,328 (19.2%)	1,042 (17.0%)
>£100,000	7,941 (7.5%)	307 (5.0%)
Missing	19,527 (18.5%)	583 (9.5%)
Age in 2006 (baseline) and 2011 (first follow-up) (y)	53.7 \pm 8.3 (35.0–72.0)	61.6 \pm 7.8 (44.0–78.0)
Townsend deprivation index at recruitment (Baseline <i>n</i> = 105,648, 99.9%; first follow-up <i>n</i> = 6,138, 99.9%)	−0.4 \pm 3.4 (−6.3–10.2)	−1.8 \pm 3.0 (−6.2–9.2)
Environmental variables		
Nighttime aircraft noise 2006 (dB)		
<45	92,367 (87.3%)	—
\geq 45 to <50	7,829 (7.4%)	—
\geq 50 – <55	3,841 (3.6%)	—
\geq 55	1,733 (1.6%)	—
Nighttime aircraft noise 2011 (dB)		
<45	93,492 (88.4%)	5,904 (96.1%)
\geq 45 to <50	7,383 (7.0%)	190 (3.1%)
\geq 50 to <55	3,491 (3.3%)	39 (0.6%)
\geq 55	1,404 (1.3%)	10 (0.2%)
Nighttime road traffic noise (dB)		
<45	44,474 (42.1%)	2,889 (47.0%)
\geq 45 to <50	38,046 (36.0%)	2,172 (35.4%)
\geq 50 to <55	13,434 (12.7%)	669 (10.9%)
\geq 55	9,809 (9.3%)	413 (6.7%)
Missing	5 (0.0%)	0 (0.0%)
Nighttime rail traffic noise (dB)		
<45	102,627 (97.0%)	6,020 (98.0%)
\geq 45 to <50	1,672 (1.6%)	54 (0.9%)
\geq 50 to <55	882 (0.8%)	48 (0.8%)
\geq 55	589 (0.6%)	21 (0.3%)
Average annual PM _{2.5} concentration ($\mu\text{g}/\text{m}^3$) (Baseline <i>n</i> = 104,318, 98.6%; first follow-up <i>n</i> = 6,127, 99.7%)	10.2 \pm 1.0 (8.2–20.7)	10.1 \pm 1.0 (8.2–18.9)
Average annual NO ₂ concentration ($\mu\text{g}/\text{m}^3$)	37.4 \pm 10.1 (4.5–79.2)	31.0 \pm 7.0 (5.3–61.8)

Table 1. (Continued.)

Variable name	Baseline (instance 0: 2006–2010) N = 105,770	First follow-up (instance 1: 2012–2013) N = 6,143
Greenspace percentage, buffer 1,000 m (%) (Baseline n = 104,795, 99.1%; first follow-up n = 6,107, 99.4%)	34.0 ± 17.5 (4.4–98.1)	40.4 ± 20.0 (8.0–98.1)
Covariates		
Ever seen a psychiatrist or doctor (GP) for nerves, anxiety, tension or depression		
No	69,598 (65.8%)	4,057 (66.0%)
Yes	34,223 (32.4%)	2,042 (33.2%)
Missing	1,949 (1.8%)	44 (0.7%)
Smoking		
Never	56,981 (53.9%)	3,616 (58.9%)
Previous	35,914 (34.0%)	2,189 (35.6%)
Current	11,917 (11.3%)	324 (5.3%)
Missing	958 (0.9%)	14 (0.2%)
Alcohol consumption		
Daily or almost daily	23,671 (22.4%)	1,185 (19.3%)
3 or 4 times a week	22,887 (21.6%)	1,594 (25.9%)
Once or twice a week	23,862 (22.6%)	1,566 (25.5%)
1–3 times a month	11,164 (10.6%)	676 (11.0%)
Special occasions only	13,104 (12.4%)	682 (11.1%)
Never	10,437 (9.9%)	439 (7.1%)
Missing	645 (0.6%)	1 (0.0%)
Vigorous or moderate physical activity per week (in days, range) (Baseline n = 102,658; 97.1%; first follow-up n = 6,083; 99.0%)	3.7 ± 2.3 (0.0–7.0)	3.8 ± 2.2 (0.0–7.0)
Time at current address (years) (Baseline n = 102,071; 96.5%; first follow-up n = 6,047; 98.4%)	17.3 ± 11.7 (1.0–70.0)	22.6 ± 12.8 (1.0–79.0)
Body mass index (kg/m ²) (Baseline n = 104,731; 99.0%; first follow-up n = 6,124; 99.7%)	27.2 ± 4.8 (12.6–68.1)	26.9 ± 4.7 (14.9–58.9)
Moderators or mediators		
Presence of hearing difficulties		
No	73,468 (69.5%)	3,899 (63.5%)
Having hearing difficulties or completely deaf	23,524 (22.2%)	1,916 (31.2%)
Missing	54 (0.1%)	4 (0.1%)
Nightshift work		
Sometimes, usually or always	5,393 (5.1%)	163 (2.7%)
Never/rarely, do not know, prefer not to answer, did not answer or	100,377 (94.9%)	5,980 (97.3%)
Never moved since recruitment		
Yes	76,883 (72.7%)	4,660 (75.9%)
No	28,880 (27.3%)	1,483 (24.1%)
Missing	7 (0.0%)	0 (0.0%)
Looking after home/family ^a		
Yes	6,025 (5.7%)	234 (3.8%)
No or missing	99,745 (94.3%)	5,909 (96.2%)
Diabetes ^b		
Yes	6,278 (5.9%)	394 (6.4%)
No	98,492 (93.1%)	5,742 (93.5%)
Missing	1,000 (0.9%)	7 (0.1%)
Hypertension ^c		
Yes	53,690 (50.8%)	3,562 (58.0%)
No	51,949 (49.1%)	2,581 (42.0%)
Missing	131 (0.1%)	0 (0.0%)
Dementia ^d		
Yes	1,605 (1.5%)	91 (1.5%)
No or missing	104,165 (98.5%)	6,052 (98.5%)
Sleep disorder ^e		
Yes	4,028 (3.8%)	129 (2.1%)
No or missing	101,742 (96.2%)	6,014 (97.9%)

Note: This table displays mean ± SD (min-max) [n, % of N] for continuous variables, or n (% of N) for categorical variables. All actimetric outcomes were measured at one time point (2013–2015) and are presented in the baseline column, as they were linked to the baseline UK Biobank assessments. Aircraft noise levels for 2006 are also in the baseline column because they were only used with baseline data. Aircraft noise levels for 2011 are included in both baseline and first follow-up columns, because they were used with baseline for actimetric measures and with first follow-up for self-reported measures. —, no data; dB, decibel; NO₂, nitrogen dioxide; PM_{2.5}, fine particulate matter with aerodynamic diameter ≤ 2.5 μm; SD, standard deviation.

^aLooking after home/family is a labor market status. It means the participant who were neither employed nor unemployed due to home/family responsibilities.

^bDiabetes was self-reported at baseline based on doctor diagnosis.

^cHypertension was based on self-reported doctor-diagnosed cases at baseline, self-reported use of medication to treat hypertension at baseline, or recorded blood pressure readings showing systolic blood pressure ≥ 140 or diastolic blood pressure ≥ 90 at baseline.

^dDementia was identified using multiple ascertainment sources from baseline through 2020.

^eSleep disorders were based on self-report, primary care diagnosis or hospital diagnosis up to 2023.

Analytic Results

Actimetric measured outcomes. The final number of participants involved in regressions using actimetric outcomes was 18,398–18,399. The loss of participants is due to missing covariates. Figure 3 (Table S4) shows that individuals exposed to L_{night}

≥ 55 dB exhibited 0.12 mg (95% CI: 0.013, 0.23) higher average acceleration during the least active 8-h period than those exposed to < 45 dB. A similar pattern of association was seen when looking at ≥ 45 dB to < 50 dB or ≥ 50 dB to < 55 dB. These overall findings present a gradient, indicating that risks rose with increasing noise level.

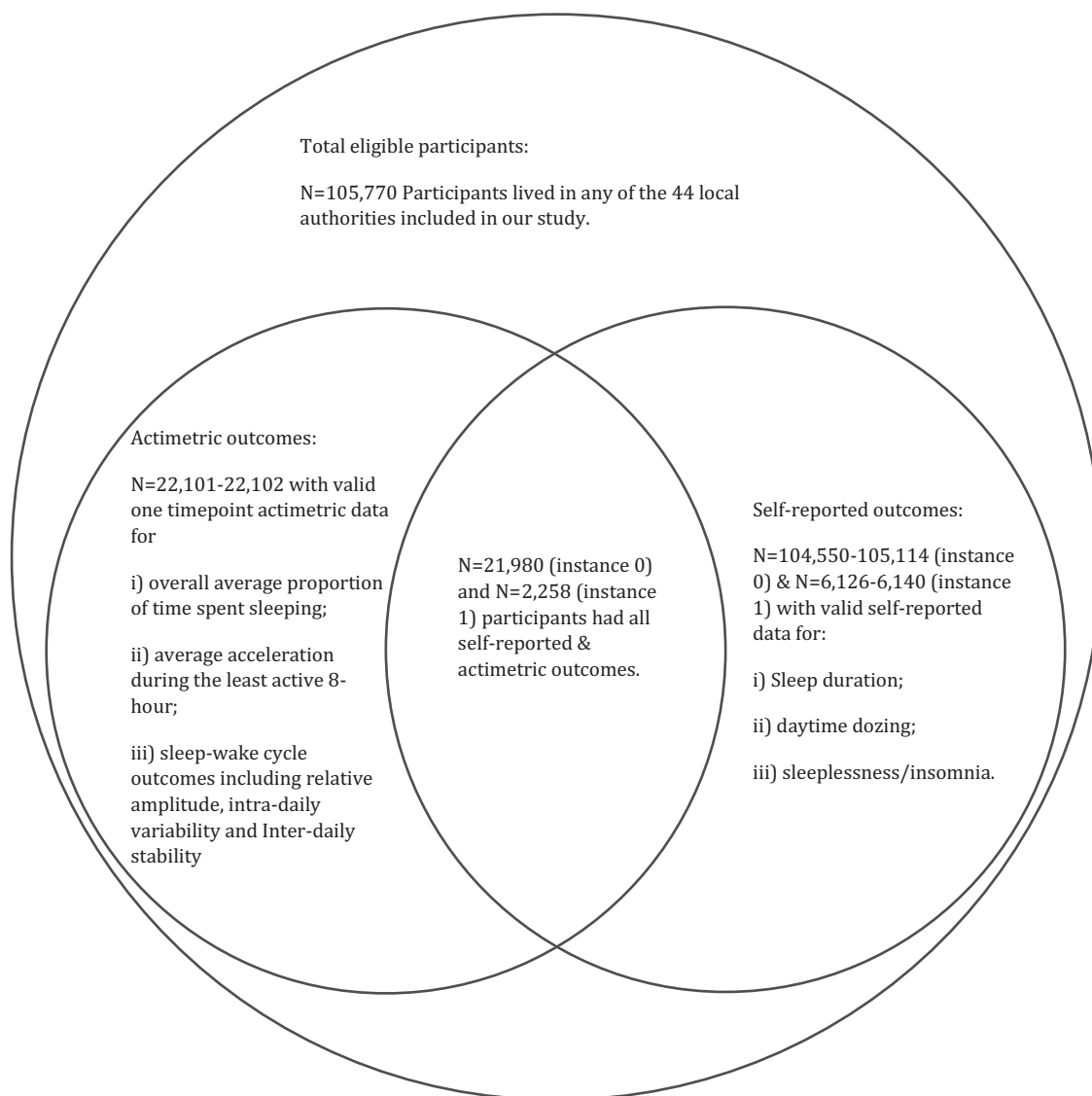


Figure 2. Venn diagram depicting the number of UK Biobank participants with valid values for each outcome.

From actimetry data, individuals exposed to noise levels ≥ 55 dB spent $\sim 0.7\%$ (95% CI: 0.6%, 0.7%) more time on average on sleep or in bed, equivalent to ~ 10 min per day in comparison with those exposed to <45 dB (Table S5). Conversely, for those exposed to noise levels ≥ 50 dB to <55 dB, there was an approximate 0.6% lower (~ 8 min) in average sleep or bed time (95% CI: -0.9% , -0.3%).

Figure 4 presents sleep-wake cycle results. Gradients with increasing noise levels were seen for all three sleep-wake cycle outcomes. For relative amplitude (Table S6), when compared with participants exposed to <45 dB, higher L_{night} was associated with a lower RA by -0.003 (95% CI: -0.005 , -0.002 ; ≥ 45 dB to <50 dB), -0.004 (95% CI: -0.005 , -0.003 ; ≥ 50 dB to <55 dB), and -0.006 (95% CI: -0.007 , -0.005 ; ≥ 55 dB), respectively, where negative values indicate higher levels of activity during sleep and/or lower activity during the day.

Moreover, intradaily variability (IV) measures were higher by 0.006 (95% CI: -0.001 , 0.013; ≥ 45 dB to <50 dB), 0.008 (95% CI: 0.002, 0.015; ≥ 50 dB to <55 dB), and 0.021 (95% CI: 0.019, 0.023; ≥ 55 dB), respectively, where positive values indicate a more fragmented sleep-wake rhythm indicative of circadian dysfunction (Table S7).

Interdaily stability (Table S8) had a lower level by -0.008 (95% CI: -0.010 , -0.006 ; ≥ 50 dB to <55 dB), and -0.010 (95% CI: -0.014 – 0.006 ; ≥ 55 dB), respectively, where negative values indicate weaker alignment with light and other environmental cues that regulate the biological clock.

Self-reported outcomes. A total of 84,537 to 84,759 participants had full observations and were involved in regressions using self-reported outcomes. Results from repeated cross-sectional analysis (Figure 5; Table S9) shows among participants exposed to noise levels of 55 dB or higher nighttime aircraft noise, there was a 13% higher likelihood of reporting sleeplessness sometimes or usually (OR = 1.13; 95% CI: 0.92, 1.39) in comparison with individuals exposed to noise levels below 45 dB, albeit with wide confidence intervals. When looking at daytime dozing reported by $\sim 3\%$ of the study population (Table 1; Table S10), those exposed to noise levels of 55 dB or higher had an $\sim 52\%$ higher likelihood (OR = 1.52; 95% CI: 1.32, 1.75). No association was found between nighttime noise and self-reported sleep duration (Table S11) due to large uncertainty.

Sensitivity analysis. We performed analyses on subsets of the sample that excluded individuals prone to noise misclassification. The results are presented in Figures S2–S9 (Table S4–S11), with

Outcome: average acceleration and proportion of time spent on sleep or in bed

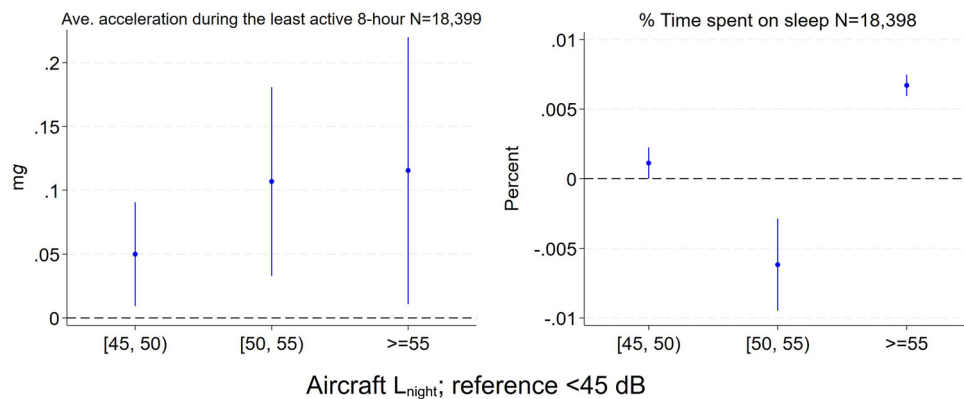


Figure 3. Cross-sectional association between nighttime aircraft noise and actimetry data on average acceleration, measured in milligravitational units (mg) during the least active 8 h, and percentage of time spent on sleep or in bed using UK Biobank cohort ($n = 18,398$ – $18,399$). Note: The figures display the point estimate (β), and 95% CIs. β represents the increment in the absolute value of the outcome when exposed to higher aircraft noise categories, in comparison with those exposed to <45 dB. L_{night} refers to the A-weighted equivalent noise level (L_{eq}) measured in decibels (dB) over the 8-h night period from 23:00 hours to 07:00 hours. All models have been adjusted for sex; ethnicity; age in 2006; BMI; ever seen a psychiatrist or doctor (GP) for nerves, anxiety, tension, or depression; smoking status; alcohol consumption; total number of vigorous or moderate physical activities (in days) a participant typically reported doing in a week; average yearly household income before tax; Townsend deprivation index at recruitment by place of residence; nighttime road traffic noise; nighttime rail traffic noise; NO_2 concentration; $PM_{2.5}$ concentration; and greenspace percentage within a buffer of 1,000 m. The numeric results can be found in Excel Tables S1 and S2. BMI, body mass index; CI, confidence interval; GP, general practitioner.

each graph including the previously presented results from the full sample as a reference. The findings from these sensitivity analyses remain consistent with the main results, suggesting our conclusions are robust to different types of potential exposure misclassification.

In subset analyses considering demographic and sociodemographic factors that might influence susceptibility to sleep disturbances, the results are presented in Figures S10–S17 (Table S4–S11). Most subgroups showed broadly similar patterns of associations with actimetric data as those in main results, but with varying coefficient sizes and less clear patterns, likely related to smaller sample size. There was no evidence that those with lower income or in non-White ethnic groups were experiencing disproportionate

impacts. However, we did find that elderly individuals exposed to $L_{night} \geq 55$ dB had an approximate 5.4% higher (~ 1 h and 8 min within a 24-h period on average) actigraphy-measured sleep duration.

In the third set of sensitivity analyses (Figures S18–S25; Table S4–S11), we examined participants reporting health conditions known to be linked to sleep problems. Analyses of actimetric data suggested potential vulnerabilities among participants with diabetes, dementia, or sleep disorder, although based on smaller numbers with wide confidence intervals. We found people with diabetes or dementia exposed to noise levels ≥ 55 dB (in comparison with <45 dB) exhibited significantly lower relative amplitude, with associations being ~ 11 and 17 times higher than those found

Outcome: sleep-wake cycle change; $N=18,399$

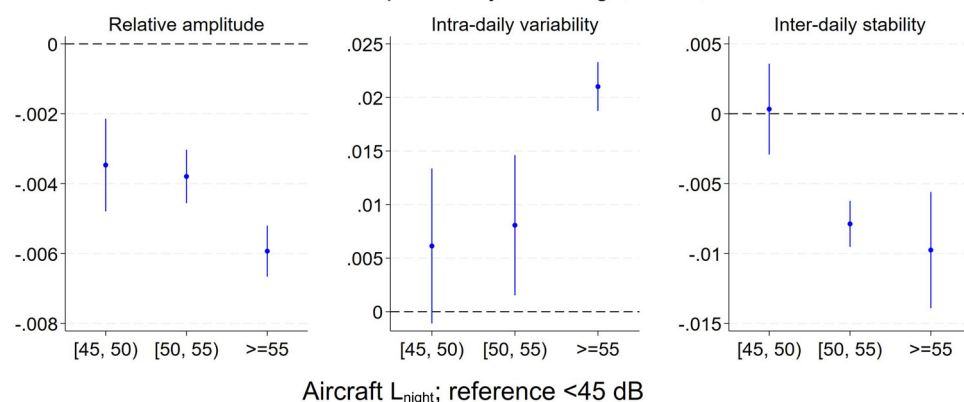


Figure 4. Cross-sectional association between nighttime aircraft noise and sleep-wake cycle using UK Biobank cohort ($n = 18,399$). Note: Sleep-wake cycle outcomes including RA, IV, and IS, all unitless. A higher RA value indicates greater activity during the day and reduced activity during sleep. A high IV suggests a more fragmented rhythm indicative of circadian dysfunction. A higher IS score indicates a strong alignment with light and other environmental cues that regulate the biological clock. The figures display the point estimate (β) and 95% CIs. β represents the increment in the absolute value of the outcome when exposed to higher aircraft noise categories, in comparison with those exposed to <45 dB. L_{night} refers to the A-weighted equivalent noise level (L_{eq}) measured in decibels (dB) over the 8-h night period from 23:00 hours to 07:00 hours. All models have been adjusted for sex; ethnicity; age in 2006; BMI; ever seen a psychiatrist or doctor (GP) for nerves, anxiety, tension, or depression; smoking status; alcohol consumption; total number of vigorous or moderate physical activities (in days) a participant typically reported doing in a week; average yearly household income before tax; Townsend deprivation index at the time of recruitment from the national census output areas associated with the participant's place of residence; nighttime road traffic noise; nighttime rail traffic noise; NO_2 concentration; $PM_{2.5}$ concentration; and greenspace percentage within a buffer of 1,000 m. The numeric results can be found in Excel Tables S3, S4, and S5. BMI, body mass index; CI, confidence interval; GP, general practitioner; IS, interdaily stability; IV, intradaily variability; RA, relative amplitude.

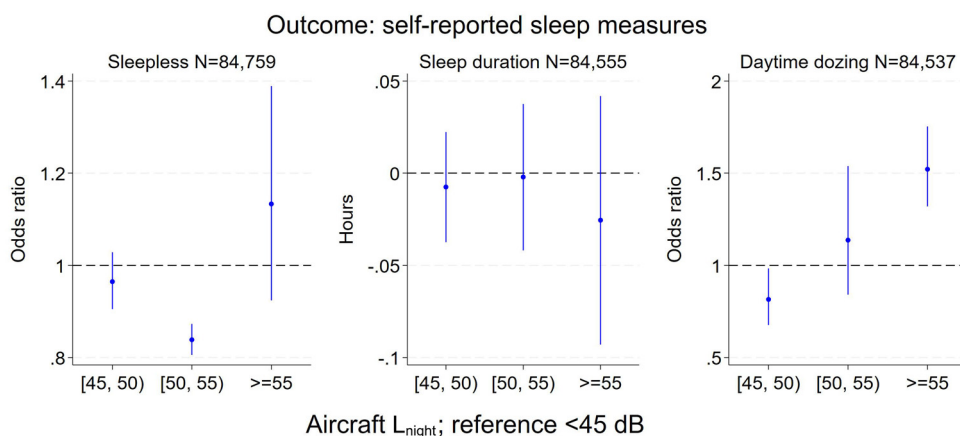


Figure 5. Repeated cross-sectional association between nighttime aircraft noise and self-reported sleep outcomes using UK Biobank cohort ($n=84,537$ – $84,759$). Note: The figures “Sleepless” (left) and “Daytime Dozing” (right) illustrate the ORs and 95% CIs, whereas the “Sleep Duration” (middle) figure presents the point estimate (β) and 95% CIs. The OR represents the likelihood of someone reporting more severe sleep disturbance outcomes when exposed to noise levels ≥ 55 dB in comparison with those exposed to <45 dB; β represents the increment in the absolute value of the outcome when exposed to higher aircraft noise categories, in comparison with those exposed to <45 dB. L_{night} refers to the A-weighted equivalent noise level (L_{eq}) measured in decibels (dB) over the 8-h night period from 23:00 hours to 07:00 hours. All models have been adjusted for sex; ethnicity; age in 2006 and 2011; BMI; ever seen a psychiatrist or doctor (GP) for nerves, anxiety, tension, or depression; smoking status; alcohol consumption; total number of vigorous or moderate physical activities (in days) a participant typically reported doing in a week; average yearly household income before tax; Townsend deprivation index at the time of recruitment from the national census output areas associated with the participant’s place of residence; nighttime road traffic noise; nighttime rail traffic noise; NO_2 concentration; $\text{PM}_{2.5}$ concentration; and greenspace percentage within a buffer of 1,000 m. The numeric results can be found in Excel Tables S6, S7, and S8. BMI, body mass index; CI, confidence interval; GP, general practitioner; OR, odds ratio.

in the entire sample. Diabetic participants exposed to aircraft $L_{\text{night}} \geq 55$ dB also demonstrated the highest intradaily variability and lowest interdaily stability, with effect sizes estimateId between 6 and 10 times greater than the pooled effects when all participants were included. The odds for participants with a sleep disorder who were exposed to ≥ 55 dB, in comparison with those with a sleep disorder but exposed to <45 dB, was 300% higher. They also spent nearly 24 min (longest among all subgroups) more in sleep or in bed.

Discussion

Many studies relying on subjective reports of sleep quality have found that aircraft noise is associated with disturbed sleep. This study is one of the first to provide objective evidence of impacts of aircraft noise on sleep using actimetry data, with particular strengths of a very large sample size and recruitment being independent of interest in aircraft noise.

Specifically, we observed a higher level of average acceleration during the least active 8-h period in individuals exposed to the highest levels of aircraft noise in comparison with those in the lowest noise group. We also saw sleep–wake cycle changes. Participants exposed to higher nighttime aircraft noise experienced a diminished contrast between daytime activity and nighttime rest (as measured by relative amplitude).⁵¹ Their rest–activity rhythm was less stable and less synchronized with the 24-h light–dark cycle (as measured by interdaily stability).^{21,52} They also showed fragmented rest–activity rhythm (as measured by intradaily variability).^{52,53} However, we found aircraft noise had no clear impact on objectively measured length of time on sleep or in bed, which agrees with findings on noise exposure and self-reported sleep length in our and other studies.¹²

Our results on self-reported outcomes suggest mixed results. We noted that nighttime aircraft noise was associated with daytime dozing, with a substantial association size, which again suggests some evidence of poor nighttime sleep among people exposed to high level of aircraft noise at night.^{27,54} However, although we found a slightly higher likelihood of self-reported sleeplessness among people exposed to higher

levels of aircraft noise, such an association was not statistically significant. Furthermore, self-reported shorter hours of sleep were observed among those exposed to high noise levels, which contrasts with our previous evidence of a slightly longer time sleep or in bed measured actimetrically.

Several factors could contribute to differing results from actimetric and self-reported outcomes. Sleep is an unconscious process, and its subjective evaluation can be challenging.⁸ The potential for recall bias in self-reported sleep measures may account for the contrasting evidence observed. In particular, when looking at self-reported sleep duration, people may not estimate their sleep well and/or estimate it to whole numbers (e.g., 7 h, 8 h), and some may have included daytime naps in the total reported sleep duration. The algorithm used for actimetric defined sleep duration from an Oxford group²⁰ may include time in bed and is less strict than some algorithms.^{55,56} This approach may lead to a classification bias: an individual who is immobile yet awake can be inaccurately categorized as being in a sleep phase.¹² Some studies have found substantial differences between self-reported and physiologically derived measures of sleep, including those related to noise-induced sleep disturbance.^{8,57} For example, a 2017 study (DEBATS Study) conducted in France with 1,244 participants living near three airports discovered that an increase of 10 dB(A) in aircraft noise level at night was associated with an OR of 1.63 (95% CI: 1.15, 2.32) for self-report of sleeping <6 h during the sleeping period of the day.²⁶ However, a subset of 112 individuals with actimetric data showed longer total sleep time (TST) and time in bed (TB) among those exposed to high levels of aircraft noise.¹²

Given the more objective nature of actimetric measures, evidence of aircraft noise association with actigraphy-derived sleep measures based on a large-scale cohort can complement current studies that predominantly use subjective measures. We showed that actigraphy provides detailed and subtle sleep measures that are not captured by questionnaires. Future research is recommended to examine the association between noise exposure from not only aircraft but also road and railway sources and actimetric measures of sleep disturbance, sleep efficiency, and staging in large cohorts.

Our findings may have a broader health implication. Nighttime exposure to aircraft noise was associated with a slightly higher average acceleration, indicating a higher level of participant movement during rest periods.^{18,19} We observed a 0.12 mg difference in those exposed to higher aircraft noise over the least active 8 h, which compares to an average acceleration in the least active 8 h in the UK Biobank cohort of 3.8 mg. The differences are small, and, at present, it is unclear how meaningful they may be, because little research has been conducted on this measure to date.

However, one previous study found that a higher level of participant movement during rest periods of +0.4 mg was linked to a higher risk of adverse outcomes from COVID-19.¹⁸ A +1.5 mg increase in acceleration (the SD difference) was associated with a 3.0 cm increase in waist circumference adiposity, a 0.9% increase in % fat, a 0.2-point decrease in fitness as measured by the Short Physical Performance Battery (SPPB) score, a reduction of 1.4 repetitions in the sit-to-stand test, and an increase of 1.5 bpm in resting heart rate.⁵⁸

To interpret findings on RA, we looked at previous studies. One study using UK Biobank data (91,105 participants) found that a one-quintile reduction (~ -0.02 to -0.05 difference in absolute value) was associated with increased risks of lifetime major depressive disorder (OR = 1.06; 95% CI: 1.04, 1.08), lifetime bipolar disorder (OR = 1.11; 95% CI: 1.03, 1.20) and greater mood instability (OR = 1.02; 95% CI: 1.01, 1.04).⁵⁹ A pooled analysis across three studies involving 578 healthy participants showed individuals with the least robust 24-h rest–activity pattern (bottom quintile of relative amplitude) had a BMI that was 2.65 kg/m² higher than those with the most robust pattern (top quintile).^{60,61} Another UK Biobank study found that RA 1 SD higher than the mean ($\sim +0.02$) was associated with ~ 5 cm lower waist circumference.⁵⁸ If these results can be directly compared with our findings, our identified differences (-0.006) in RA would correspond to an approximate increase of 1.5 cm in waist circumference among individuals exposed to noise levels ≥ 55 dB in comparison with those exposed to levels < 45 dB. Specific subgroups like individuals with diabetes (-0.06) and those who look after home/family (-0.02) showed greater differences in RA when exposed to nighttime aircraft noise, which are in the range previously associated with mental health effects.⁵⁹

With respect to interdaily stability/intra-daily variability, a study from the United States that focused on 1,734 elderly individuals (≥ 65 y of age) found a more stable 24-h activity rhythm (as measured by interdaily stability) was associated with a lower mortality risk [hazard ratio (HR) = 0.83; 95% CI: 0.71, 0.96] per 1 SD (approximately 0.1), whereas a more fragmented rhythm as measured by IV was associated with a higher mortality risk (HR = 1.22; 95% CI: 1.04, 1.44) per 1 SD (around 0.1).⁶² We found in our study that elderly participants (≥ 65 y of age), exposed to aircraft noise ≥ 55 dB L_{night} , had an associated 0.08 increase in IV. If results can be directly compared and associations are causal, our results might imply a comparable increase in mortality ratio related to fragmented activity rhythms. This implication needs to be investigated in follow-up studies.

Interdaily stability values are also associated with metabolic health. A 2020 literature review reported that among a subgroup of 1,137 older individuals, higher interdaily stability values (suggesting greater stability of 24-h rest–activity patterns), were associated with 31%, 27%, and 24% lower odds of having metabolic syndrome, type-2 diabetes, and obesity, respectively.^{61,62}

Disruption of circadian rhythms is of concern because of the potential for wider health impacts.⁶³ There is robust evidence derived from both animal models and human epidemiological research that demonstrates circadian disruption to be significant risk factors for cardiovascular disease,⁶⁴ and growing interest in

the relationship between environmental noise and cancer, particularly breast cancer.^{65,66} One theory for this link is the reduction in melatonin levels caused by disrupted circadian rhythm, which may subsequently contribute to an increased cancer risk.^{65,67} Circadian misalignment and diminished amplitude of rhythms have been demonstrated to predict the onset of neurodegenerative diseases.⁶⁸ This pathway could again potentially explain the largely unknown mechanisms underlying the association between noise exposure and neurodegenerative disorders such as dementia, a topic that has attracted increasing attention in recent years.^{69–72} Additional studies are needed to establish whether nighttime aircraft noise may be impacting on melatonin levels, and circadian rhythm.

A key strength of our paper lies in the large sample size, which, to the best of our knowledge, is the largest to date to look at aircraft noise and device-based measures of sleep disturbance. Although a large sample size can raise concerns about overpowered statistical analysis, we conducted multiple sensitivity analyses on subsamples with smaller sample sizes, and our results remained largely consistent. The research design involving self-reported outcomes is repeated cross-sectional, which is another strength. Furthermore, actimetry has been widely used and validated¹⁰ and provides rich outcomes that may not be available through questionnaires. Our study serves as a hypothesis-generating investigation to explore potential actimetric derived outcomes that could be used as proxies for sleep disturbance in future noise studies.

Our paper has some limitations. First, there may be misclassification of noise levels, which could affect the accuracy of our findings. In particular, the noise contours used were assessed for 2011, whereas actimetric data were measured between 2013 and 2015. In addition, building sound-proofing is likely to vary and create differences in individual exposures.⁸ We adopted a complete case approach to analyze the data, which could introduce bias.⁷³ Some unmeasured health or disease variables might have influenced the sleep outcomes, which we were unable to adjust for in our study. Our sleep outcomes may be subject to biases. Different devices and algorithms used to process actigraphy data could introduce bias. An individual who was immobile may be classified as being in a sleep phase even when they were awake, or conversely, someone with a sleep disorder could be classified as awake, due to movement, despite being asleep.^{12,15} There was uncertainty about how to address negative values during the gravity removal process, as well as the best method to identify non-wear episodes.¹⁵ However, actigraphy has the advantage of being easily performed in larger samples while preserving participants' natural sleep habits in their homes.¹² Some studies, including a retrospective analysis involving 27 patients, have shown that actigraphy and ambulatory polysomnography can yield comparable results in assessing chronic insomnia.⁷⁴ In a meta-analysis of eight studies that compared sleep architecture estimates between wrist-worn actigraphy and polysomnography, authors found that actigraphy-based sleep staging had some ability to classify different sleep stages in comparison with polysomnography.^{75,76}

We note that flight activity at all the airports in our study is increasing, so consideration will need to be given to potential for increased noise exposure and associated public health impacts. Heathrow, Gatwick, Birmingham, and Manchester, among many other major airports in Europe, are set to expand to accommodate an anticipated increase in passenger numbers by nearly 42% from 2017 to 2040, as projected by the European Environmental Agency.⁷⁷ Heathrow is planning to build a third runway, supported by the UK government through the Airports National Policy Statement.⁷⁸ Gatwick plans to make more regular use of its Northern Runway,⁷⁹ and Manchester and Birmingham airports are considering transforming or expanding their terminals.^{80,81}

Conclusion

We know from many studies relying on subjective report of sleep quality that aircraft noise is associated with disturbed sleep. This study is one of the first to provide evidence on the association between aircraft noise and objective measures of sleep using actimetry data from a large sample near four major international airports in England. Aircraft noise at night was associated with increased movement during the least active continuous 8-h periods (a proxy for sleep) and a disrupted sleep–wake cycle, which has been associated with wider health impacts including mental health, BMI, diabetes, and mortality risk. However, we found aircraft noise had minimal impact on objectively measured length of time in bed, which agrees with self-reported sleep length in our and other studies. Our results have significant policy implications, highlighting the necessity for authorities to formulate strategies that mitigate sleep disturbances caused by aircraft noise.

Acknowledgments

The authors thank Enock Havyarimana for help with data preparation. The authors also thank members of the RISTANCO advisory board for their input on the methodological aspects of this study. The advisory board includes representation from relevant government departments and agencies, community groups, nongovernmental organizations, and industry. The views expressed in this paper are those of the author(s) and may not reflect those of the advisory board members or their respective organizations.

The research was funded by the National Institute for Health and Care Research (NIHR) Leicester Biomedical Research Centre (BRC). Additional funding support came from the NIHR Health Protection Research Unit (HPRU) in Environmental Exposures and Health, a partnership between the UK Health Security Agency (UKHSA), the Health and Safety Executive (HSE), and the University of Leicester (Grant number: NIHR200901). The views expressed are those of the author(s) and not necessarily those of the NIHR, Department of Health and Social Care, UKHSA, HSE or University of Leicester.

This research has been conducted using the UK Biobank Resource under Application Number 59129.

The authors gratefully acknowledge the UK Civil Aviation Authority who provided aircraft noise data, calculated using the UK Civil Aircraft Noise Model, ANCON, and the Noise and Statutory Nuisance Team at the Department for Environment, Food & Rural Affairs (DEFRA), for the creation and provision of the Environmental Noise (England) Regulations Round 2 exposure surfaces of rail transport in England.

Funder acknowledgment for NIHR HPRU: The research was supported by the NIHR HPRU in Environmental Exposures and Health, a partnership between the UKHSA, the HSE, and the University of Leicester. The views expressed are those of the author(s) and not necessarily those of the NIHR, UKHSA, HSE, or University of Leicester. [Grant number NIHR200901]

Funder acknowledgment for NIHR BRC: This study/project is funded by/supported by the NIHR Leicester Biomedical Research Centre (BRC). The views expressed in this publication are those of the author(s) and not necessarily those of the National Institute for Health and Care Research or the Department of Health and Social Care.

Data acknowledgment for aircraft noise: The authors acknowledge the UK Civil Aviation Authority, who provided aircraft noise data, calculated using the UK Civil Aircraft Noise Model, ANCON.

Data acknowledgment for railway noise: The authors gratefully acknowledge the Noise and Statutory Nuisance Team at the DEFRA, for the creation and provision of the Environmental Noise

(England) Regulations Round 2 exposure surfaces of rail transport in England.

A.L.H. conceived the study. A.L.H. and X.G. developed the study design. J.G., C.J., and K.A. prepared the exposure data and the environmental confounder data. G.A., K.E., and X.G. prepared and manipulated the UK Biobank data with advice from A.R. on sleep and actimetric data. X.G. ran the analyses and wrote the initial draft with input from A.L.H. All authors contributed to interpretation of the results and provided comments on subsequent drafts.

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