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Occupational electromagnetic field exposure and sleep disturbances: The predominant role of high-frequency electric fields

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ABSTRACT

Electromagnetic fields (EMFs) are ubiquitous and include low-frequency magnetic fields (LF-MF) from alternating currents, low-frequency electric fields (LF-EF) from wiring and equipment, and high-frequency electric fields (HF-EF) from wireless technologies and broadcast antennas. Bus drivers are exposed to an EMF mixture and report higher rates of sleep disorders than the general population. This study aimed to examine associations between sleep disturbances and cumulative occupational EMF exposure over 12 months, considering individual components and the mixture.

EMF exposure estimates from the Swiss bus-exposure matrix were matched to the occupational history of 351 TRAPHEAC study bus drivers. Sleep quality, insomnia, and excessive daytime sleepiness (EDS) were assessed using the Global Sleep Assessment Questionnaire. Associations with cumulative EMF exposure were evaluated using multivariable linear regression controlled for age, sex, occupational noise, and nightshift work, and heat exposure. Mixture effects were analyzed with Bayesian Kernel Machine Regression (BKMR), and the influence of non-occupational EMF exposure was examined via stratification.

Multivariable linear regression showed positive associations of HF-EF, but not LF-EF or LF-MF, with insomnia and EDS, although models explained little variance. BKMR confirmed the predominance of HF-EF in the mixture effect, with a positive but statistically non-significant dose-response for the EMF mixture. Stratified analyses suggested stronger associations among drivers with low non-occupational EMF exposure.

These findings suggest a dose-response relationship between occupational EMF mixture exposure and sleep disturbances, primarily driven by HF-EF. However, the overall variance explained by EMF exposure is small, highlighting the role of other risk factors in sleep disturbances among bus drivers.

1. Introduction

Sleep constitutes a fundamental component of daily life, playing a pivotal role in maintaining homeostasis and health (Irwin, 2015). Recognized as an underappreciated public health problem, sleep disturbances are a major risk factor for cardiovascular diseases, metabolic disorders, and mortality (The Lancet, 2022). Chronic sleep disturbances adversely affect neurological functioning such as memory formation, sustained attention and other higher cognitive functions (Bijlsma et al., 2024). Given their high prevalence, sleep disturbances cause much distress to both sufferers and their bed partners and have far-reaching effects on population health and economic wellbeing. For example, insomnia occurs in up to a third of adults and in 50% of primary care patients (Perlis et al., 2022). Excessive daytime sleepiness is another frequent sleep disorder, with reported prevalence of 2.5-33%, depending on the population studied and the definition and measurement used (Pérez-Carbonell et al., 2022).

Sleep disturbances are particularly prevalent among professional drivers (Faria et al., 2024; Remy and Guseva Canu, 2023) and were identified as the major cause of road accidents. It is estimated that approximately 20–50% of road traffic accidents are attributable to driver sleepiness (Davidović et al., 2018).

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Considering the critical role of safe public road transport in promoting environmental sustainability and protecting public health, it is essential to investigate and prevent sleep disorders among public bus drivers. Indeed, these disorders are multifactorial, resulting from the interaction of sleep-related, occupational, and health-related determinants. Sleep-related factors include circadian misalignment, such as working during the biological night and attempting to sleep during the biological day, as well as insufficient sleep duration and poor sleep quality (Pérez-Carbonell et al., 2022). Work-related factors encompass extended working hours, night shifts, irregular schedules, and insufficient recovery time between shifts (Mohamed et al., 2012). Health-related factors involve underlying sleep disorders (e.g., insomnia, obstructive sleep apnea), comorbid medical conditions, and adverse lifestyle behaviors (Faria et al., 2024).

Beyond these well-established determinants, emerging research has suggested that environmental and occupational exposures may also contribute to sleep disturbances. In this context, several authors have raised the question of a potential causal role of exposure to electromagnetic fields (EMF) in the onset and persistence of sleep disorders (Bosch-Capblanch et al., 2024; Huss et al., 2015; Liu et al., 2014; Mann and Röschke, 2004; Mohler et al., 2010, 2012), particularly in light of the substantial increase in radiofrequency (RF) exposure in everyday life (Bandara and Carpenter, 2018).

This issue appears especially relevant for bus drivers, who have been identified since the early 2000s among the highly exposed workers with respect to extremely low-frequency magnetic fields (LF-MF) (Deadman, 2002) and whose occupational EMF exposure levels may increase with the progressive replacement of combustion-engine buses with hybrid and electric vehicles.

In everyday environments, general population exposures are dominated by LF-MF from building wiring and power lines, low frequency electric fields (LF-EF) from household voltage potentials, and RF from personal wireless devices and ambient telecommunication networks (Sagar et al., 2018).

Transport microenvironments, however, present more complex exposure profiles, because multiple EMF sources coexist. Public transport vehicles, including buses, trams, and commuter trains, are characterized by a combination of LF-MF, LF-EF, and RF exposures. Measurement campaigns in Europe have consistently shown that extremely low frequency magnetic fields ELF-MF levels in electric and hybrid buses, as well as trolleybuses, can be substantially higher than background residential levels, with local magnitudes approaching or occasionally exceeding the current exposure limits (Icnirp, 2020) during operation near high-current power electronics (Mazurek et al., 2024). RF exposures within these vehicles are dominated by personal devices, embedded Wi-Fi routers, and fleet communication systems, complemented by ambient downlink signals from base stations (Chiaramello et al., 2019; Loizeau et al., 2023).

Buses exhibit heterogeneous EMF exposure patterns depending on propulsion type and internal electrical architecture (Ahsan and Celik, 2024). Conventional internal combustion engine buses typically produce minimal LF-MF beyond the 12V electrical subsystem. Hybrid buses, integrating regenerative braking systems and high-voltage batteries, generate additional LF-MF and LF-EF components, while fully electric buses and trolleybuses rely on high-capacity battery packs and inverters, producing spatially complex LF-MF distributions within the cabin (Mazurek et al., 2024; Ahsan and Celik, 2024).

Simultaneously, RF exposure levels in all bus types are influenced by passenger and operator mobile device usage, onboard Wi-Fi networks, and communication links to fleet management systems or external control centers. The evolution of bus technology has introduced increasingly sophisticated electronic systems that contribute to the in-cabin EMF environment. Modern buses are equipped with advanced driver assistance systems (Krummenacher et al., 2025), including radar-based collision avoidance, lidar proximity sensing, and algorithmic driving correction modules (Celaya-Echarri et al., 2019). These systems operate across high and intermediate frequency bands, generating localized emissions in the driver cabin. Additionally, vehicle dashboards now integrate a wide array of electronics: GPS navigation, digital instrumentation, telematics, two-way radios for safety and coordination with depots or police, and wireless communication modules for passenger information systems. Collectively, these sources expand both the high and low frequency EMF exposure landscape in ways that were negligible in earlier vehicle generations (Mazurek et al., 2024; Loizeau et al., 2023; Gryz et al., 2022).

Bus drivers, who spend prolonged time within the vehicle cabin, represent a population at risk of higher cumulative EMF exposure compared to passengers or the general population, raising concerns about potential impacts on sleep quality, neurocognitive function, and other physiological processes. Therefore, this study aimed to examine the dose-response relationship between occupational exposure to EMF and sleep quality in a cohort of Swiss bus drivers, considering the LF-MF, LF-EF, and RF exposure first as independent exposure components and then as a mixture.

2. Methods

2.1. Source population and study sample

The study population stems from the Transport Personnel Health Cohort (TRAPHEAC) study (Guseva Canu and Remy, 2025). The first recruitment campaign ran from June to October 2024, and the follow-up questionnaire was sent 12 months later (in June 2025). Study data comprise information collected at baseline.

The TRAPHEAC study protocol and data collection are described in detail elsewhere (Guseva Canu and Remy, 2025). Briefly, all bus drivers living in Switzerland were eligible to participate. The online baseline questionnaire has been developed in collaboration with unions and bus drivers and administered via REDCap software (Harris et al., 2009). The questionnaire contained four sections: (1) demographic (e.g., sex, age, marital status), (2) detailed history of employment and driven buses and work conditions and (e.g., work hours, work environment, type of route), (3) health (e.g. musculoskeletal disorders, sleep disorders), and (4) lifestyle (e.g., nutrition, physical activity) (Guseva Canu, 2025).

At the moment of analysis (November 2025), the TRAPHEAC study counted 748 registered participants. However, not all of them completed the Inclusion questionnaire, and some did it partially and left some sections incomplete. Because the main missingness concerned the outcome and main exposure variables, imputation was not considered appropriate. Therefore, the study sample consists of TRAPHEAC participants with complete data on study variables.

2.2. Outcome definition and measurement

We considered three outcomes, one general, the global sleep assessment score (GSA), and two corresponding to specific sleep disorders: insomnia and excessive daytime sleepiness (EDS). Insomnia is defined as a disturbance of sleep continuity reflected by pathological alterations in sleep latency, number of awakenings, wake after sleep onset, total sleep time, or sleep efficiency, and accompanied by daytime impairments such as sleepiness, fatigue, somatic complaints, mood disturbance, cognitive or occupational dysfunction, or dissatisfaction and concerns about sleep (Perlis et al., 2021). EDS is defined as the inability to stay awake and alert during major waking episodes (the longest period in 24 h that a person would typically be awake), resulting in periods of irrepressible need for sleep or unintended lapses into drowsiness or sleep (Pérez-Carbonell et al., 2022).

To identify these outcomes, we used the Global Sleep Assessment Questionnaire (GSAQ) (Roth et al., 2002), which is considered as the most suitable screening tool for clinical practice, given its clinimetric quality, comprehensiveness, and brevity (Perlis et al., 2021, 2022; de Villiers et al., 2024; Klingman et al., 2017; Sibley et al., 2025). The

GSAQ consists of 11 items. Each item asks about a possible symptom the respondent may have experienced in the previous 4 weeks and is answered using a 4-point scale (with response options of *never, sometimes*, *usually*, and *always*). Hence, the possible global score range is 15–60, with higher values indicating greater possibility of the presence of a sleep disorder and low sleep quality. The instrument's developers reported that it has good internal consistency (Cronbach $\alpha = 0.76$), test-retest reliability ranging from 0.51 to 0.92 over a period of 7–14 days, and good convergent and divergent validity (Roth et al., 2002). The GSAQ was validated against polysomnography (Sibley et al., 2025) and cross-culturally, showing acceptable internal consistency (Cronbach $\alpha = 0.73$), high intra-class-correlation value (ICC = 0.82), good convergent validity with the Pittsburgh Sleep Quality Index (Taziki et al., 2025), and good criterion validity (Siegel, 2022).

The GSAQ allows screening four most common sleep disorders, including insomnia and EDS (Perlis et al., 2022). As there is an item overlap for some of these disorders and no validated cutoffs to score their severity, we used the factor analysis (Tavakol and Wetzel, 2020), as described by Remy et al. (Remy et al.). The four-factor model, consistent with the current clinical GSAQ use (Perlis et al., 2021, 2022; de Villiers et al., 2024; Klingman et al., 2017; Sibley et al., 2025), was identified. For each factor (representing a specific sleep disorder), we calculated a continuous score by attributing a value between 1 ("usually) and 4 ("always") and then computing the weighted average based on the factor analysis. To facilitate the result interpretability, we scaled the insomnia and EDS severity scores to have a range from 0 to 100, with higher scores indicating a higher risk of sleep problems.

2.3. Occupational EMF and noise exposure assessment

The exposure levels to high-frequency (100 kHz to 7 GHz) electric fields (HF-EF in V/m), low-frequency (5 to 100 kHz) electric fields (LF-EF in V/m), low-frequency (5 to 100 kHz) magnetic fields (LF-MF in μT), and equivalent noise (dB(A)) for different bus models, driven by study participants in the 12 months preceding the sleep quality assessment, were extracted from the bus-exposure matrix (BEM) (Remy et al., 2025a) and matched with the work history completed in the framework of the TRAPHEAC study. The BEM was developed by modeling exposure values measured in a representative sample of buses, reflecting the technological evolution of the Swiss bus fleet, using the Integrated Nested Laplace Approximation (Rue et al., 2009). These models were then applied to the entire Swiss bus fleet. LF-EF and LF-MF were recorded in stationary buses with the engine running and no occupant present in the driver's cabin. Measurements were conducted using a PMM 8053 probe (PMM S.r.l), positioned at the approximate location of the driver's torso. This static measurement configuration was dictated by technical constraints of the instrument, which cannot be operated reliably under dynamic conditions and requires a minimum distance of 3 m from any individual to avoid interference. Under these conditions, the recorded LF exposure levels were considered to represent baseline emissions from the vehicle. HF-EF and noise levels were measured within the bus driver's cab during trips in both urban and rural settings.

Exposure values were derived by linking individual bus driving histories with the BEM. In the BEM, all occupational exposures were expressed as 8-h time-weighted average (TWA) exposure levels for a standard working day. Furthermore, the BEM distinguished between the urban route (in cities, with a stop every 1-3 min and a maximal speed of 50 km/h) and regional route (intra-villages, with driving time between stop up to 15 min and a maximal speed of 80 km/h). The nature of the exposure estimates in the BEM allowed calculation of time-weighted average exposures by combining exposure measurements from different bus models according to their duration of operation during the relevant time period. For each participant, a 12-month average exposure was computed as a weighted average of the exposure levels assigned to each bus model driven during the preceding twelve months, with weights defined by the duration of use of each model and adjusted for the participant's work rate. For exposure to HF-EF and noise, the type of road (urban and regional) associated with each bus model was additionally considered. The HF-EF and LF-EF are expressed in V/m, the LF-MF in μT, and the noise in dB(A). On average, the participants drove 2.2 (SD = 1.2) bus models, and in maximum 6 different bus models in 2024.

2.4. Residential EMF exposure assessment

As residential exposure to EMF could affect the sleep quality independently and thus modify its association with occupational EMF, we constructed residential exposure indices based on participants' self-reported information on the presence, and use, of electronic devices in the home and bedroom environment, patterns of mobile phone use, and bedtime habits regarding device proximity.

Two separate indices were created to represent the dominant physical exposure domains: 1) radiofrequency electric fields (RF-EF) associated primarily with wireless communication devices and 2) extremely low-frequency magnetic fields (ELF-MF) generated by electrical appliances and household wiring. Each exposure component was approximated using simplified models combining representative field magnitudes reported in the literature with reported durations or frequencies of device use. Contributions from different devices were combined to estimate daily exposure proxies expressed in units proportional to field intensity multiplied by duration (V/m·h equivalents for RF-EF and μT·h equivalents for ELF-MF). Representative field strengths and scaling coefficients were derived from published exposure measurements and international guideline reports (NIH, 2022; Wall et al., 2019; WiFiinschools.org.uk, 2018; Zeleke et al., 2021; Protection, 2020; World Health Organization, 2007; National Research Council, 1997).

Because these indices are intended to approximate relative rather than absolute exposure levels, the resulting composite residential RF-EF and ELF-MF exposure scores were normalized to a 0–100 scale within the study population. This transformation preserved the ranking of participants while facilitating comparison across components. The indices were not interpreted as direct measures of physical exposure and were not included as exposure variables in the mixture analyses. The electric component was selected a priori given a stronger body of literature regarding its effect on sleep (Association, 2012; Belpomme and Irigaray, 2020; Pall, 2016) and, consequently, a potentially stronger modifying effect in the relationship between occupational EMF exposures and sleep outcomes. Participants were classified into two groups representing lower and higher residential exposure using the median value of the private electric field index. The median split was chosen to ensure balanced group sizes and stable estimation in subgroup analyses. A detailed description of the variable construction, parameter values, and literature sources is provided in the Supplementary Materials File S1.

2.5. Heat wave exposure assessment

Elevated night-time temperatures have been consistently associated with shorter sleep duration, delayed sleep onset, and reduced deep sleep across large-scale observational studies using millions of nights of sleep recordings (Li et al., 2025; Minor et al., 2022). Therefore, we considered exposure to a heat wave during the week preceding the sleep outcome assessment as potential confounder or moderator of EMF-sleep relationship. The heat wave presence was ascertained using participants' individual data, namely the place of residence and the date of GSAQ completion, combined with regional meteorological data provided by the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss).

MeteoSwiss database comprises daily temperature measurements (minimum, mean, and maximum) across 12 selected stations in Switzerland (Federal Office of Meteorology and Climatology MeteoSwiss, 2026a). According to MeteoSwiss criteria, a heat wave was defined as at least three consecutive days with a mean daily

temperature of 25°C or higher (Federal Office of Meteorology and Climatology MeteoSwiss, 2026b). For each participant, exposure to a heat wave during the period of interest was determined by assessing whether the meteorological station closest to their place of residence recorded at least three consecutive days with a mean temperature ≥ 25°C. A total of seven participants were exposed to days during which the mean temperature was ≥ 25°C, however, none of the participants was exposed to a heat wave as defined by MeteoSwiss (Federal Office of Meteorology and Climatology MeteoSwiss, 2026b).

2.6. Covariates

Covariates were selected a priori based on published evidence on determinants of sleep quality and sleep disorders in working populations, particularly drivers. The selected covariates were sex and age (Suh et al., 2018; Zeng et al., 2020). Furthermore, occupational exposure to noise (in dB(A)) and to night shiftwork (average number of night shifts per week) were considered as potential confounders (Cho et al., 2023; Da Silva et al., 2025; Lim et al., 2020). Average number of work hours per day, average number of workdays per week, work rate, and the proportion of driving time in urban areas have been integrated in the BEM construction (Remy et al., 2025b) and occupational exposure modelling.

2.7. Statistical analysis

2.7.1. Multivariable linear regression analyses

To evaluate associations between occupational EMF exposures and sleep outcomes under parametric assumptions, multivariable linear regression models were fitted including the three occupational exposure components (HF-EF, LF-EF, and LF-MF) simultaneously and serially adjusted for covariates and potential confounders. Furthermore, the analysis was repeated after stratification of the study sample in subsamples with high and low residential exposure to investigate potential heterogeneity in the association between occupational EMF exposures and sleep outcomes according to background residential EMF exposure. Finally, as only seven participants were identified as having been exposed to at least one day with a mean temperature ≥ 25°C prior to the GSAQ completion, we repeated the analysis on a subsample excluding these participants to test the model sensitivity.

All exposure variables were modelled as continuous predictors on their original measurement scales (EF in V/m and MF in μT), for each of considered outcomes: GSA score, insomnia severity score, and EDS severity score, multivariable linear regression models were used.

Regression coefficients represent the expected change in the outcome associated with a one-unit increase in the corresponding exposure variable, holding other exposures and covariates constant. Statistical significance was evaluated using two-sided tests with $\alpha = 0.05$.

2.7.2. Bayesian Kernel Machine Regression (BKMR)

To assess potential joint, non-linear, and non-additive effects of occupational EMF exposures, BKMR models were implemented using the *bkmr* R package. BKMR models the relationship between multiple correlated exposures and an outcome using a flexible non-parametric exposure-response surface defined through a Gaussian process prior (Bobb et al., 2018). This approach allows the joint effect of multiple exposures to be estimated without specifying explicit interaction terms.

The mixture included three occupational exposure components: HF-EF, LF-EF, and LF-MF. Age, sex, noise and nightshift work were controlled by adjustment. The 7 participants exposed to days with temperatures ≥ 25°C were excluded from the analysis. A Gaussian kernel was used to construct the exposure covariance matrix. Models were estimated using Markov Chain Monte Carlo (MCMC) sampling for 10,000 iterations, with the first 5000 iterations discarded as burn-in. Convergence was assessed through visual inspection of trace plots and evaluation of chain mixing.

Continuous outcomes were standardized prior to analysis to facilitate comparison across models and to improve numerical stability of the Gaussian process estimation. Consequently, BKMR estimates represent changes in the outcome expressed in standard deviation units.

Variable selection was not used because preliminary runs yielded posterior inclusion probabilities equal to one for all exposure variables.

Several graphical summaries were used to characterize the exposure–response surface. Univariable exposure-response functions were estimated by varying one exposure across its observed range while holding the remaining exposures at their median levels. Bivariable exposure surfaces were examined by simultaneously varying two exposures while fixing the third at its median value. The overall mixture effect was evaluated by estimating the change in outcome associated with increasing all mixture components simultaneously across quantiles of their joint distribution. Following conventions used in previous BKMR studies (Bobb et al., 2018; Liu et al., 2018), R mixture contrasts corresponding to an increase from the 25th to the 75th percentile of the joint and individual exposure distribution were reported.

2.7.3. Bayesian Kernel Machine Regression with group structure (BKMR-GS)

To investigate potential heterogeneity in the association between occupational EMF exposures and sleep outcomes according to background residential RF-EF exposure, we used a novel BKMR extension, BKMR-GS, using the bkmrGS R package (Dematteis et al., 2025). BKMR-GS incorporates a separable kernel that allows estimation of group-specific exposure-response functions while sharing selected parameters across groups (Dematteis et al., 2025). This approach enables the exposure-response surface to vary across predefined strata while maintaining statistical efficiency by sharing smoothing parameters, covariate effects, and residual variance across groups (Dematteis et al., 2025). The residential RF-EF exposure was used exclusively to structure the kernel function and was not included as an exposure in the mixture.

The exposure mixture and analytical procedure were the same as those described for the BKMR analysis (section 2.7.2). Group-specific exposure-response functions and mixture effects were estimated separately within each residential exposure group. Differences between groups were assessed descriptively through comparison of the shapes and magnitudes of the estimated exposure-response functions.

Visualization of bivariable exposure surfaces in BKMR-GS requires computationally intensive kernel matrix inversion. To maintain feasible computation times, raster plots were generated using 100 posterior samples. These figures are intended for descriptive visualization of the exposure–response surface within the Bayesian workflow rather than formal statistical inference (Gabry et al., 2019). All model inferences were based on the full post-burn-in MCMC chains.

3. Results

3.1. Description of the study population

The study sample comprised 345 participants with complete data on study variables (Table 1). Supplementary Material Table S1 provides sex-specific descriptive statistics on exposure and outcome variables. Males constituted around 84% of the sample and the mean age was 49 years. On average, participants reported working 3.5 nights or early morning shifts per week. None was exposed to noise nor to EMF at the level above the Swiss occupational exposure limits.

More than 80% of participants reported having a Wi-Fi box in their bedroom, and about 60% have had at least one electric shock. The characteristics of subsamples stratified by residential RF-EF exposure are quite similar regarding the occupational exposures (Table 1). However, participants with high residential RF-EF exposure had higher sleep outcomes scores and were younger than those with low exposure.

Table 1
Characteristics of the study population (TRAPHEAC, N = 345).

Variables	Study sample (N = 345)	Subsample with low residential EF exposure (N = 193)	Subsample with high residential EF exposure (N = 152)
	N (%)/Mean (SD; Min-Max) [P25; P75; P90][a]	N (%)/Mean (SD; Min-Max)[P25; P75; P90][a]	N (%)/Mean (SD; Min-Max)[P25; P75; P90][a]
Sex Female	56 (16.2)	34 (17.6)	22 (14.5)
Sex Male	289 (83.8)	159 (82.4)	130 (85.5)
Age in years	49.04 (9.55; 26.35-65.31)	51.65 (8.26; 26.35-65.31)	45.72 (10.06; 26.4-64.12)
Heat wave (at least 1 day > 25°C)	7 (2)	6 (3.1)	1 (0.7)
N. days > 25°C	0.02 (0.17; 0-2)	0.04 (0.21; 0-2)	0.01 (0.08; 0-1)
Perceived occupational stress (−)	3.11 (1; 1-5)	3.12 (1.01; 1-5)	3.09 (1; 1-5)
N. night-early morning shifts/ week	3.5 (2.06; 0-10)	3.53 (2; 0-10)	3.47 (2.15; 0-10)
Sleep outcomes			
Global sleep assessment score	22.34 (4.9; 15-42)	21.81 (4.43; 15-38)	23.03 (5.37; 15-42)
Insomnia score	25.49 (15.45; 0-80.7)	23.84 (14.84; 0-70.06)	27.58 (15.99; 0-80.7)
Excessive daytime sleepiness score	25.52 (15.61; 3.45-84.66)	24.17 (14.87; 3.45-84.66)	27.24 (16.39; 4.41-81.8)
Occupational exposures			
High-frequency electric fields (V/ m)	0.38 (0.21; 0.03-1.48) [0.25; 0.46; 0.61]	0.37 (0.22; 0.03-1.37) [0.25; 0.46; 0.6]	0.38 (0.21; 0.06-1.48) [0.26; 0.45; 0.63]
Low-frequency electric fields (V/ m)	0.4 (0.13; 0.04-0.65) [0.33; 0.46; 0.51]	0.4 (0.13; 0.04-0.65) [0.32; 0.46; 0.53]	0.4 (0.12; 0.04-0.65) [0.33; 0.46; 0.47]
Low-frequency magentic field (μT)	0.16 (0.08; 0.01-0.68) [0.09; 0.23; 0.25]	0.16 (0.08; 0.01-0.45) [0.09; 0.24; 0.25]	0.17 (0.08; 0.01-0.68) [0.09; 0.23; 0.25]
Equivalent noise (dB (A))	65.45 (12.14; 5.58-79.07) [64.42; 71.88; 74.03]	64.78 (12.79; 5.58-77.5) [62.08; 71.93; 74.27]	66.3 (11.25; 6.99-79.07) [66.24; 71.64; 73.96]
Private source of EMF			
WIFI box in bedroom	286 (82.9)	163 (84.5)	123 (80.9)
Principal phone use: phone call	55 (15.9)	28 (14.5)	27 (17.8)
Past electric shock	206 (59.7)	117 (60.6)	89 (58.6)
Electric radiator use (≥1 h/week)	8 (2.3)	4 (2.1)	4 (2.6)
Drill use (≥1 h/ week)	20 (5.8)	11 (5.7)	9 (5.9)
Hair dryer use (≥1 h/ week)	63 (18.3)	29 (15)	34 (22.4)
Induction stove use (≥1 h/week)	110 (31.9)	57 (29.5)	53 (34.9)
Magnetic mattress (≥1 h/week)	3 (0.9)	2 (1)	1 (0.7)
Use electric device in bed (≥1 h/week)	12 (3.5)	3 (1.6)	9 (5.9)
N. electric devices in bedrrom	2.08 (1.39; 0-7)	1.81 (1.19; 0-7)	2.43 (1.54; 0-7)
N. emitting devices in bedroom	1.61 (1.3; 0-7)	1.08 (1; 0-2)	2.28 (1.32; 0-7)
N. hour of phone use/ day	2.54 (1.59; 0.5-6)	1.81 (1.17; 0.5-6)	3.47 (1.57; 0.5-6)
N. hour of phone call/day (near head)	0.24 (0.45; 0.01-2.5)	0.07 (0.08; 0.01-0.5)	0.46 (0.6; 0.01-2.5)
N. hour without screen before bed	0.77 (0.58; 0.5-4.5)	0.85 (0.63; 0.5-4.5)	0.66 (0.51; 0.5-3.5)
Brain exposure to electric fields (V/m · h)	2.71 (4.99; 0.08-37.5) [0.08; 2.5; 7.5]	0.79 (0.94; 0.08-5) [0.08; 0.92; 1.38]	5.14 (6.71; 0.08-37.5) [0.92; 5.62; 15]
Body exposure to electric fields (V/m · h)	1.27 (0.79; 0.25-3) [0.75; 1.75; 3]	0.9 (0.58; 0.25-3) [0.75; 1.25; 1.75]	1.73 (0.78; 0.25-3) [1.25; 2.25; 3]
Electric fields in bedroom (V/m · h)	4.87 (2.48; 0-16) [2; 6; 6]	3.84 (1.88; 0-6) [2; 6; 6]	6.17 (2.55; 0-16) [6; 6; 9.6]
Electric fields due to phone before bed (V/m · h)	2.56 (0.86; 0.33-3) [3; 3; 3]	2.41 (0.94; 0.33-3) [1; 3; 3]	2.76 (0.69; 0.43-3) [3; 3; 3]
Total exposure to electic fields (V/m · h)	11.41 (6.39; 3.33-47.75) [7.83; 12.75; 17.1]	7.95 (2.14; 3.33-10.67) [6.33; 9.83; 10.67]	15.8 (7.24; 10.75-47.75) [11.33; 16.27; 24.25]
Electric score (0-100) (−)	18.18 (14.38; 0-100) [10.13; 21.2; 30.99]	10.39 (4.81; 0-16.51) [6.75; 14.63; 16.51]	28.07 (16.3; 16.7-100) [18.01; 29.13; 47.09]
Electric score: high	152 (44.1)	0 (0)	152 (100)
Electric score: low	193 (55.9)	193 (100)	0 (0)
Magnetic field in bedroom (μT · h)	1.67 (1.11; 0-5.6) [1.6; 1.6; 3.04]	1.45 (0.95; 0-5.6) [1.6; 1.6; 1.6]	1.95 (1.23; 0-5.6) [1.6; 1.6; 4]
Magnetic field from electric radiator (μT · h)	0.01 (0.09; 0-0.6) [0; 0; 0]	0.01 (0.09; 0-0.6) [0; 0; 0]	0.02 (0.1; 0-0.6) [0; 0; 0]
Magnetic field from magnetic mattress and other bed deveices (μT · h)	0.17 (0.82; 0-4) [0; 0; 0]	0.1 (0.64; 0-4) [0; 0; 0]	0.26 (0.99; 0-4) [0; 0; 0]
Magnetic field from high-field appliances (μT · h)	0.41 (0.54; 0-1.83) [0; 1; 1.33]	0.37 (0.52; 0-1.83) [0; 1; 1]	0.45 (0.55; 0-1.83) [0; 1; 1.33]
Magnetic field from past electric shock (μT · h)	0.06 (0.05; 0-0.1) [0; 0.1; 0.1]	0.06 (0.05; 0-0.1) [0; 0.1; 0.1]	0.06 (0.05; 0-0.1) [0; 0.1; 0.1]
Total exposure to magnetic field (μT · h)	2.32 (1.53; 0-11.43) [1.6; 2.7; 4.1]	2 (1.2; 0-6.7) [1.6; 2.6; 3.18]	2.74 (1.79; 0-11.43) [1.7; 3.03; 5.69]
Magnetic score (0-100) (−)	20.32 (13.4; 0-100) [13.99; 23.62; 35.86]	17.47 (10.5; 0-58.6) [13.99; 22.74; 27.81]	23.95 (15.67; 0-100) [14.87; 26.53; 49.77]
Magnetic score: high	164 (47.5)	77 (39.9)	87 (57.2)
Magnetic score: low	181 (52.5)	116 (60.1)	65 (42.8)

[a] 25th, 75th, and 90th percentiles reported for occupational and residential exposure to EMF.

3.2. Multivariable linear regression results

Table 2 shows that the HF-EF exposure was positively associated with all sleep outcomes in a clear and statistically significant dose-response manner and this result was robust to the serial adjustment. In the fully adjusted model, increasing HF-EF exposure was associated with increase in GSA score (β = 3.15; 95%-CI: 0.25; 6.05 per V/m), insomnia score (β = 9.81; 95%-CI: 0.75; 18.86 per V/m) and EDS score (β = 9.45; 95%-CI: 0.24; 18.66 per V/m).

In contrast, LF-MF exposure tended to show inverse and statistically non-significant associations with sleep outcomes.

These results remained unchanged after exclusion of 7 participants with exposure to high temperature (Tables S2 and S3).

The stratified analyses (Table 2, Models 3a and 3b) showed that non-occupational EMF exposure acts as effect modifier of the dose-response relationship between occupational exposure to EMF components and sleep outcomes. Indeed, the relationship with HF-EF is consistently stronger in bus drivers with low residential exposure to EMF.

Table 2
Multivariable linear regression models for the association between EMF exposure variables and sleep-related outcomes (TRAPHEAC, N = 338).

Outcome	Eposure	Model 1: unadjusted		p-value	Model 2: adjusted for age, sex, noise and night shifts			Model 3a: Model 2 stratified by residential electric exposure (high)			Model 3b: Model 2 stratified by residential electric exposure (low)		
		β	95% CI (low; up)		β	95% CI (low; up)	p-value	β	95% CI (low; up)	p-value	β	95% CI (low; up)	p-value
Global Sleep Assesment score	HF-EF (V/m)	2.80	(-0.14; 5.73)	0.06	3.15	(0.25; 6.05)	**0.03**	2.83	(-1.7; 7.36)	0.22	3.16	(-0.57; 6.9)	0.10
	LF-EF (V/m)	0.83	(-4.56; 6.22)	0.76	1.62	(-4.32; 7.56)	0.59	8.30	(-0.78; 17.39)	0.07	−3.65	(-10.12; 2.83)	0.27
	LF-MF (μT)	−5.66	(-13.45; 2.13)	0.15	−7.23	(-14.98; 0.52)	0.07	−13.68	(-25.7; −1.65)	**0.03**	−1.42	(-11.43; 8.59)	0.78
	Model adjusted R2: 0.01				*Model adjusted R2: 0.04*			*Model adjusted R2: 0.06*			*Model adjusted R2: 0.01*		
Insomnia score	HF-EF (V/m)	8.80	(-0.44; 18.04)	0.06	9.81	(0.75; 18.86)	**0.03**	8.73	(-4.57; 22.03)	0.20	10.92	(-1.5; 23.34)	0.08
	LF-EF (V/m)	2.43	(-14.54; 19.41)	0.78	2.98	(-15.53; 21.5)	0.75	19.99	(-6.71; 46.68)	0.14	−8.70	(-30.22; 12.81)	0.43
	LF-MF (μT)	−10.90	(-35.44; 13.64)	0.38	−16.18	(-40.37; 8.01)	0.19	−32.07	(-67.38; 3.24)	0.07	−1.58	(-34.83; 31.68)	0.93
	Model adjusted R2: 0.00				*Model adjusted R2: 0.06*			*Model adjusted R2: 0.09*			*Model adjusted R2: 0.02*		
Excessive Daytime Sleepiness score	HF-EF (V/m)	8.06	(-1.31; 17.42)	0.09	9.45	(0.24; 18.66)	**0.04**	3.32	(-10.54; 17.19)	0.64	14.07	(1.59; 26.54)	**0.03**
	LF-EF (V/m)	4.96	(-12.24; 22.16)	0.57	11.15	(-7.68; 29.99)	0.24	28.37	(0.54; 56.21)	**0.05**	−9.80	(-31.41; 11.82)	0.37
	LF-MF (μT)	−10.33	(-35.19; 14.54)	0.41	−15.53	(-40.14; 9.08)	0.22	−26.85	(-63.66; 9.97)	0.15	−4.97	(-38.38; 28.44)	0.77
	Model adjusted R2: 0.00				*Model adjusted R2: 0.05*			*Model adjusted R2: 0.05*			*Model adjusted R2: 0.02*		

3.3. BKMR results

BKMR models were used to evaluate the joint association between occupational EMF exposures and standardized sleep outcomes. Across the three outcomes, mixture functions suggested modest positive trends with increasing joint exposure levels, although credible intervals generally overlapped zero (Fig. 1).

For the GSA score, increasing the EMF mixture from the 25th to the 75th percentile of the joint exposure distribution was associated with a predicted increase of 0.03 standardized units, corresponding to an elevation of the GSA score by 0.13 points (~0.03x4.9, where 4.9 is the standard deviation of the GSA score) when EMF mixture exposure increases from the first to the third quartile (Fig. 1, plot A and Table 3). For insomnia, this increase in exposure mixture corresponds to 3.97% of score, and for the EDS to 5.74% of score (Fig. 1, plot B and C and Table 3).

Component-specific analysis indicated that for three outcomes, HF-EF contributed most to the positive direction of these associations, yet its effect was not statistically significant (Table 3 and Figs. S1 and S2).

Across all outcomes, univariate exposure–response functions consistently suggested a monotonic positive association with HF-EF and weak inverse or near-null associations for LF-MF and LF-EF (Fig. S3). Bivariate exposure-response surfaces indicated opposing gradients between HF-EF and LF-MF, with higher HF-EF combined with lower LF-MF corresponding to higher predicted outcome values, while surfaces involving LF-EF showed comparatively limited variation (Fig. S4).

3.4. BKMR-GS results

BKMR-GS models were used to explore whether associations between occupational EMF exposures and sleep outcomes differed according to background residential electric exposure (low vs. high, defined using the median split of the private electric proxy score). Across outcomes, the estimated mixture functions suggested modest differences between strata (Fig. S5). In general, higher levels of the occupational EMF mixture were associated with slightly higher predicted sleep

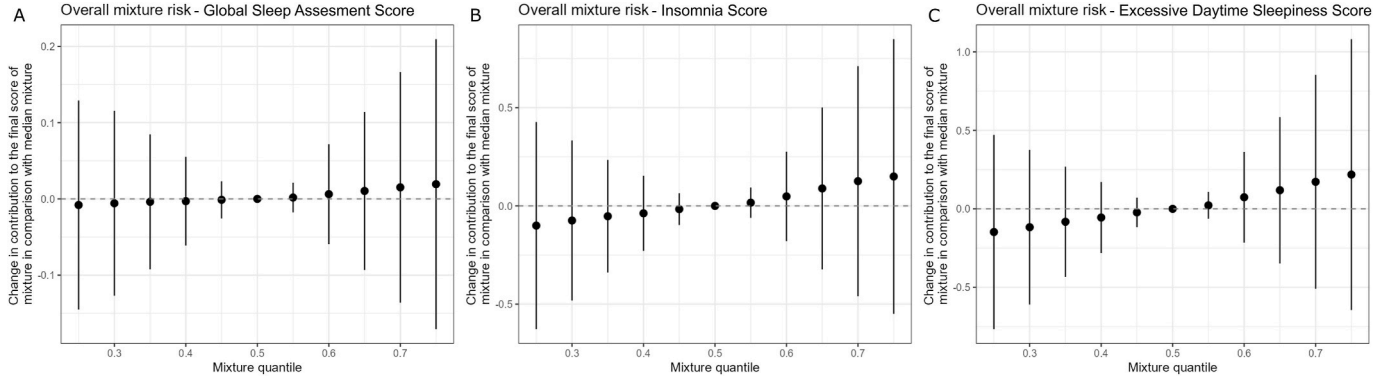


Fig. 1. Dose-response relationship between occupational exposure to EMF mixture and sleep outcomes Legend: Plot A represents the change in the standardized GSA score compared to the median mixture while changing all 3 exposures (HF-EF, LF-EF and LF-MF) from their 25th percentile to their 75th percentile in 5 percentile increases. Plot B and C present the results for the standardized insomnia score and standardized EDS score, respectively.

Table 3
Change in sleep outcomes associated with joint and component specific EMF exposure increase from 25th to 75th percentile.

Outcome	Exposure	Exposure value		Outcome (standardized values)		Outcome (original values)	
		25th percentile	75th percentile	Delta	95% CI (low; up)	Delta	95% CI (low; up)
Global Sleep Assesment score							
	Joint mixture			0.03	(-0.3; 0.35)	0.13	(-1.48; 1.75)
	HF-EF (V/m)	0.25	0.46	0.04	(-0.23; 0.31)	0.19	(-1.13; 1.5)
	LF-EF (V/m)	0.33	0.46	0.00	(-0.06; 0.06)	0.00	(-0.28; 0.28)
	LF-MF (μT)	0.09	0.23	−0.01	(-0.18; 0.16)	−0.05	(-0.9; 0.8)
Insomnia score							
	Joint mixture			0.26	(-1.06; 1.57)	3.97	(-16.42; 24.36)
	HF-EF (V/m)	0.25	0.46	0.25	(-0.92; 1.42)	3.91	(-14.2; 22.02)
	LF-EF (V/m)	0.33	0.46	0.02	(-0.37; 0.4)	0.26	(-5.65; 6.17)
	LF-MF (μT)	0.09	0.23	−0.01	(-0.4; 0.37)	−0.20	(-6.13; 5.73)
Excessive Daytime Sleepiness score							
	Joint mixture			0.37	(-1.12; 1.85)	5.74	(-17.5; 28.98)
	HF-EF (V/m)	0.25	0.46	0.34	(-0.97; 1.64)	5.27	(-15.19; 25.73)
	LF-EF (V/m)	0.33	0.46	0.04	(-0.42; 0.5)	0.62	(-6.65; 7.88)
	LF-MF (μT)	0.09	0.23	−0.01	(-0.42; 0.4)	−0.15	(-6.56; 6.27)

impairment in the low residential exposure group. Mixture functions appeared flatter or negative at higher exposure quantiles in the high residential EMF exposure group. However, credible intervals generally overlapped zero, indicating substantial uncertainty in the estimated mixture effects.

Similarly to the linear regression results, the component-specific BKMR-GS analysis suggested that HF-EF tended to show more positive associations with sleep outcomes in the low residential EMF exposure group (Fig. S6).

4. Discussion

4.1. Summary of study findings and internal consistency

Both linear regression and BKMR analyses consistently showed a positive dose-response relationship between occupational exposure to HF-EF and all considered sleep-related outcomes: GSA, insomnia, and EDS. In the linear regression models, this relationship was statistically significant and robust to control for occupational exposure to noise and to night shift work intensity, residential EMF exposure, and heatwave occurrence in the seven days preceding the sleep quality assessment. The BKMR analysis confirmed the positive dose-response trends between occupational exposure to EMF as a mixture for all three outcomes although without reaching statistical significance.

Within this framework, HF-EF emerged as the most influential component of occupational EMF exposure across outcomes, consistently defining the dominant axis of variation in the exposure–response surfaces. LF-MF showed stable inverse associations, suggesting a modifying or counterbalancing role. LF-EF demonstrated sensitivity to the exposure context, with detectable effects mainly in individuals with low residential EMF exposure.

The stronger exposure–response gradients observed in low residential EMF exposure strata provide evidence of effect modification by non-occupational EMF exposures. In contrast, the attenuation of occupational exposure–response relationships in high residential EMF exposure strata suggests exposure saturation or a masking effect of non-occupational sources, limiting the detectability of occupational exposure effects.

The consistently low linear regression adjusted R^2 values (Table 2) indicate that occupational EMF exposures account for only a small share of outcome variability, highlighting the dominant role of non-occupational and individual-level factors. This finding is expected in environmental and occupational epidemiology and does not undermine the relevance of BKMR, which is designed to characterize complex, non-linear exposure–response relationships rather than to optimize predictive accuracy.

Overall, these findings suggest that occupational EMF exposures in bus cabins exert weak but structured effects on sleep-related outcomes in bus drivers, with their expression robust to controlled confounders and strongly conditioned by residential exposure levels.

4.2. External consistency of study findings

The overall evidence regarding the EMF effects on sleep is debatable (Bijlsma et al., 2024; Bosch-Capblanch et al., 2024; Bandara and Carpenter, 2018; Lewczuk et al., 2014; Melnick et al., 2025; Scarato, 2025). The joint dose–response effects of different EMF components in occupational settings have never been investigated. Most studies to date have focused on a single type of radiation within a specific frequency band. In these studies, the sleep disturbances are among the most frequently reported complaints attributed to RF-EMF exposure (Association, 2012; Belpomme and Irigaray, 2020; Pall, 2016), and several epidemiological studies indicate a strong association between RF-EMF exposure and symptom reporting (Danker-Hopfe et al., 2010; Hutter et al., 2006; Martens et al., 2017).

Most experimental studies have investigated the impact of pulse-modulated RF on sleep quality in highly controlled laboratory settings using near-head exposure to mobile phones (Bosch-Capblanch et al., 2024; Danho et al., 2025; Ohayon et al., 2019). Among them, several randomized, double-blind studies have focused on the short-term effects of RF-EMF exposure for 30 to 45 min on sleep by recording brain activity using electroencephalography (EEG) (Borbely et al., 1999; Hinrichs et al., 2005; Huber et al., 2002; Loughran et al., 2005; Lowden et al., 2011; Regel et al., 2007). Overall, these studies have consistently showed that pre-sleep exposure increased spindle-frequency power during stage 2 of non-rapid eye movement (non-REM) sleep, particularly in the first hours of the night. However, it remains unclear whether these changes in sleep EEG reflect detrimental sleep quality. Notably, two studies that observed EEG alterations following mobile phone handset exposure and that also assessed subjective sleep quality did not report significant changes in subjective sleep quality (Huber et al., 2002; Lowden et al., 2011). However, the statistical power of these studies to detect such effects on sleep quality was low because of their small sample size. Moreover, subtle effects on sleep quality may not be

observable in an unfamiliar environment of a sleep laboratory with electrodes attached to the head, particularly over a single night (Bijlsma et al., 2024; Mohler et al., 2012; Herbst et al., 2010). Other studies that reported inconsistent associations between RF exposure and sleep quality (Danker-Hopfe et al., 2016; Fritzer et al., 2007; Loughran et al., 2012; Lustenberger et al., 2013, 2015; Schmid et al., 2012; Tettamanti et al., 2020; Vecsei et al., 2018) were limited by restricted generalizability, small sample sizes, short-term exposures, or a lack of follow-up assessments.

The most recent systematic review and meta-analysis (SRMA) of experimental studies estimated standard mean differences for sleep disturbances in the general population that ranged from −0.22 to 0.20 for head exposure and from −0.15 to 0.15 for whole-body exposure (Bosch-Capblanch et al., 2024). However, this SRMA was criticized for relying on conservative methodological choices that could induce biases in the direction and strength of association towards the null (Melnick et al., 2025). Indeed, the SRMA authors acknowledged that most primary studies included in their SRMA were conducted in young, healthy volunteers, who might be more resilient to RF-EMF than the general population (Bosch-Capblanch et al., 2024). Moreover, exposure conditions were not representative of real-life conditions, differing in the duration, frequency, distance and position of the exposure source.

It is widely recognized that experimental exposure conditions are hardly comparable with real-world exposure conditions, where EMF signals are highly variable in intensity and waveform, potentially enhancing their biological activity (Panagopoulos, 2019). However, studies conducted under realistic exposure conditions with a robust methodological design are almost non-existent.

To date, we have identified only a single study that has investigated the effects of repeated four-week RF-EMF exposure (using a baby monitor emitting 2.45 GHz radiation) on sleep in healthy adults. Despite a small sample size (n = 12), the study reported statistically significant changes in EEG activity during non-REM) sleep (Bijlsma et al., 2024). Additionally, seven consecutive nights of RF-EMF exposure were associated with reductions in subjective sleep quality, as measured using the Pittsburgh insomnia rating scale, with one-third of participants scoring above the clinical threshold for insomnia risk (Bijlsma et al., 2024). Moreover, a natural experiment evaluating sleep and melatonin before and after the shutdown of a broadcast transmitter observed improvements in subjective sleep quality and normalization of melatonin secretion in susceptible individuals following RF exposure reduction (Altpeter et al., 2006).

Experimental and observational evidence examining LF-EMF and ELF-MF suggests that their effects on sleep and circadian physiology are not uniformly suppressive and may, under specific exposure conditions, be neutral or even mildly modulatory (Lewczuk et al., 2014; Danho et al., 2025; Lambrozo et al., 1996; Touitou et al., 2006; Wang et al., 2024; Woldańska-Okońska and Koszela, 2024; Woldańska-Okońska et al., 2023; Touitou and Selmaoui, 2012; Dyche et al., 2012). In animal models, the results are rather contradictory, with 18 studies showing a decrease in melatonin secretion, 3 studies showing its increase and 17 studies showing no effect or inconsistent results (Touitou and Selmaoui, 2012). Prolonged exposure to 50 or 60 Hz magnetic fields in the μT range has been reported to produce small increases in nocturnal pineal melatonin concentrations or no significant suppression, with limited impact on sleep architecture, indicating preserved circadian rhythmicity (Lambrozo et al., 1996; Touitou and Selmaoui, 2012; Dyche et al., 2012). Among human studies assessing occupational or environmental exposure to magnetic fields at low intensities, 23 studies have failed to demonstrate alterations in plasma melatonin levels, urinary 6-sulfatoxymelatonin excretion, or core circadian phase markers, whereas 10 studies have found a decreased melatonin concentration (Danho et al., 2025; Touitou and Selmaoui, 2012).

A possible change in the spatial structure of the photoreceptor pigment rhodopsin due to the electric field induced by the magnetic field has been proposed as a possible pathway (Woldańska-Okońska and Koszela, 2024; Woldańska-Okońska et al., 2023; Touitou and Selmaoui, 2012). Magnetic fields might also change either the electrical activity of the pinealocytes or their ability to produce melatonin, or both. Regarding the numerous studies performed on the effects of LF-EMF on melatonin, the differences observed between animals and humans may be due to differences in the anatomical location and configuration of the pineal gland, as well as differences in the rest-activity cycle. A different sensitivity to LF-EMF could also be part of the explanation. Some human subjects may have greater sensitivity to LF-EMF, but this is difficult to demonstrate substantial interindividual variability in plasma melatonin concentrations. In a study of workers exposed daily for up to 20 years at their workplace and at home, no adverse effect of LF-EMF on melatonin concentration or circadian rhythm was observed, suggesting that chronic LF-EMF exposure appears to have no cumulative adverse effects in human adults (Touitou et al., 2003).

In line with this framework, our results showed that the association with LF-EMF, particularly magnetic fields, exhibited a negative trend with sleep outcomes, although this association did not reach statistical significance or was of borderline statistical significance.

The results obtained in high residential EMF exposure strata are more challenging to interpret in the light of available evidence. Indeed, the association between occupational EMF exposure and sleep outcomes in the subgroup with high residential EMF exposure tended to be negative. This observation may reflect a saturation or ceiling effect, whereby chronically elevated background EMF levels reduce the sensitivity of physiological systems to additional occupational exposure. In contrast, individuals with minimal baseline EMF exposure may remain more responsive to incremental occupational exposures, resulting in detectable adverse effects on sleep. Such an effect modification aligns with mechanistic evidence indicating that melatonin secretion and circadian regulation may be more strongly influenced under conditions of low chronic EMF exposure, whereas prolonged or high-intensity exposure may elicit adaptive or desensitization responses (Danho et al., 2025; Woldańska-Okońska and Koszela, 2024; Woldańska-Okońska et al., 2023).

4.3. *Mechanistic evidence and biological plausibility of study findings*

Mechanistically, repeated RF-EMF exposure may influence sleep through multiple biological pathways. First, EMF have been suggested to disrupt circadian timing and melatonin signalling, affecting both hormone dynamics and brain electrophysiology during sleep. Biologically, sleep regulation is underpinned by endogenous circadian and homeostatic processes orchestrated by the suprachiasmatic nucleus and pineal melatonin secretion (Irwin, 2015; Siegel, 2022). Melatonin plays a central role in synchronizing sleep–wake cycles, exerting neuroprotective, antioxidant, and chronobiotic effects (Woldańska-Okońska and Koszela, 2024). Disruption of melatonin rhythms is linked to difficulty initiating sleep and EDS through downstream effects on clock gene expression and neuronal excitability. Recent reviews highlight the complexity of melatonin's physiological roles and its susceptibility to environmental perturbations, including electromagnetic influences on redox and signaling pathways (Woldańska-Okońska and Koszela, 2024; Wilkerson and McRae-Clark, 2021). Second, multi-night RF-EMF exposures can modulate neurophysiological activity, altering sleep architecture and EEG power in specific frequency bands (Mohler et al., 2010, 2012; Lewczuk et al., 2014). These changes suggest a direct effect on neuronal network activity relevant to sleep initiation and maintenance (Bijlsma et al., 2024). Finally, repeated EMF exposure may trigger cumulative autonomic and oxidative stress responses (Bijlsma et al., 2024; Melnick et al., 2025; Scarato, 2025). Such processes could elevate physiological arousal and prolong sleep onset, consistent with insomnia phenotypes observed in occupational settings (Danho et al., 2025).

These mechanisms are compatible with delayed or cumulative effects rather than solely acute responses. For example, changes in melatonin

rhythms or neurophysiological function may accrue over weeks to months of repeated exposures before manifesting as clinically relevant sleep disturbances, particularly in shift workers with irregular schedules that already challenge circadian homeostasis (Irwin, 2015; Woldańska-Okońska and Koszela, 2024; Meyer et al., 2022).

From a methodological perspective, the use of a 12-month exposure window preceding the sleep quality assessment integrates both the intensity and the duration of occupational EMF exposure, capturing a biologically plausible load rather than transient fluctuations. This retrospective exposure assessment approach aligns with conceptual models of chronic stress (Epel et al., 2018) and circadian rhythm disruption, where the long-term integration of exposure exerts a greater influence on circadian regulation than short-term peaks alone (Irwin, 2015; Lewczuk et al., 2014; Meyer et al., 2022). Moreover, averaging exposure over a sufficiently long period reduces random variability arising from irregular work schedules, which are very common in bus drivers' work, increasing the stability and interpretability of the exposure estimate. In the absence of day-specific exposure data, it is unclear whether shorter windows would capture recent exposures more directly. Nevertheless, the chronic nature of sleep dysregulation supports the appropriateness of the annual cumulative metric in this context.

While causality cannot be established in this study due to its observational nature and subjective outcome measures, our results seem biologically plausible and congruent with mechanistic pathways implicated in circadian–neuroendocrine modulation. They underscore the need for further longitudinal and mechanistic investigations that incorporate detailed temporal exposure assessment and biomarkers of circadian function.

4.4. Study strengths and limitations

As far as we know, this study is the first to assess the different components of occupational EMF exposure, considering their specific and joint effects. By using BKMR we were able to analyze this multi-exposure combination as a mixture, thereby addressing the criticism raised regarding the WHO evidence synthesis, which focused only on RF and power density (Bosch-Capblanch et al., 2024; Melnick et al., 2025). The study was nested into the prospective cohort TRAPHEAC that ensured an accurate assessment of individual work history, work and lifestyle-related variables, as well as precise individual data. As this cohort is linked to several national databases, occupational and environmental exposure came from different sources, reducing the information, common variance, and differential misclassification biases. Moreover, as participants have been blind to the study objectives, we can reasonably rule out the nocebo effect albeit using participant reported outcome measures.

The use of self-reported questionnaires for exposure and outcome assessment is often criticized for their subjectiveness, as opposed to instrumental measures, considered more objective (Guseva Canu and van der Molen, 2026;Robins et al., 2009). For the objective assessment of sleep in sleep medicine, the gold standard is the EEG or polysomnography (Irwin, 2015). However, in occupational cohort study, the use of these techniques is challenging and was not possible for logistical and budget reasons. Instead, we used the GSAQ (Roth et al., 2002), considered the most suitable screening tool for sleep disturbances in clinical practice (Perlis et al., 2021, 2022; de Villiers et al., 2024; Klingman et al., 2017; Sibley et al., 2025).

Although based on a cohort with retrospective occupational exposure assessment over the 12-month period preceding outcome assessment, the statistical analyses were essentially cross-sectional, thereby limiting causal inference regarding the association between EMF exposure and sleep disturbances. Furthermore, the sample size was relatively small, which constitutes an important limitation of this study. Indeed, out of 748 bus drivers registered as TRAPHEAC participants at the time of statistical analysis, only 345 completed all sections of the Inclusion questionnaire. This relatively low response rate may raise concerns about potential selection bias, which was carefully assessed in a parallel study (Guseva Canu et al., 2026).

The participation rate of bus drivers in the TRAPHEAC could not be precisely determined due to the use of multiple, uncontrolled dissemination channels; however, an approximate participation range of 9% to 30% may be inferred, whereby this estimate remains highly uncertain. Although rather low, it is comparable with participation rates in other recent national and international studies using email contact and electronic questionnaire for data collection (Guseva Canu et al., 2026). The comparison of sociodemographic characteristics of bus drivers in our study sample with those in the source population (data provided by the Federal Statistical Office (FSO); results not shown) revealed similar sex and age distributions. The geographical distribution of the sample differed slightly from that of the target population, with an over-representation of drivers from the German-speaking Mittelland and the Italian-speaking Ticino regions (Guseva Canu et al., 2026).

To assess whether bus drivers who refused to participate did so for health or exposure-related reasons, we asked them to complete a short 3-item non-response questionnaire. The mean career duration in non-respondents was 16.47 years (SD = 10.49). The reasons for non-participation were: "Lack of interest" (11.76%), "Insufficient time" (11.76%), "Insufficient trust in the study" (35.29%), "Other reason" (5.88%), and "Prefer not to disclose" (35.29%). For the question 'Are you in good health?', all non-respondents indicated 'Yes' or 'Rather yes'. Based on this assessment, the potential for selection bias seems limited; however, not all non-respondents completed the non-response questionnaire.

A high proportion of incomplete responses in inclusion questionnaire, especially in the latest sections of the questionnaire, like Lifestyle and Wellbeing sections including GSAQ items and some of the covariates, could also lead to the self-selection phenomenon. However, a comparison of selected sociodemographic characteristics provided by the Federal Statistical Office for all bus drivers registered as TRAPHEAC participants, revealed no difference between those who completed the inclusion questionnaire and those who did not (Guseva Canu et al., 2026). Based on this assessment, we believe that despite a small proportion of bus drivers with complete data included in this study, the selection bias is rather limited.

Although, the sample size was sufficiently large to allow stratified and group-separated BKMR analysis (Bobb et al., 2018; Dematteis et al., 2025), it might have had a limited contrast in occupational EMF exposure. As shown in Table 1, standard deviations in occupational exposure estimates for HF-EF, LF-EF, LF-MF are smaller compared to those in residential exposure estimates, suggesting that occupational exposure was more uniform across study participants. This could also explain the lack of statistical significance in the BKMR-based dose-response relationship.

Occupational EMF exposure was assessed based on the Swiss BEM rather than individual measurements. Although matrix-based exposure assessment cannot fully capture individual variability within the same bus model, the resulting measurement error is expected to be predominantly of the Berkson type, which generally reduces exposure contrast and statistical precision rather than systematically biasing exposure–response estimates (Armstrong, 1998; Guseva et al., 2010; Keogh et al., 2020). Consequently, if present, such error would be more likely to attenuate statistical power and make small associations more difficult to detect than to generate spurious associations. Moreover, the Swiss BEM differs from conventional job-exposure matrices in that exposure estimates were derived from standardized instrumental measurements and detailed technical characterization of each bus model (Remy et al., 2025a). Specifically, the BEM includes 705 bus models, each described by approximately 50 technical parameters, allowing a substantially finer characterization of the workstation (i.e., bus cabin) and, consequently, the exposure to its hazards than is typically achieved with job-exposure matrices. Although the extent to which this approach reduces exposure misclassification has not been formally evaluated, it is

likely to improve the accuracy of individual exposure assignment.

Notwithstanding, during the exposure measurement campaigns used to derive the BEM EMF exposure estimates, low-frequency fields were assessed under static conditions, due to technical constraints, whereas high-frequency electric fields were measured under dynamic conditions. This difference may limit the comparability of exposure metrics, as static measurement of low-frequency fields may not fully capture the exposure experienced by bus drivers during operation. For LF fields, dynamic driving conditions, such as acceleration or braking, might generate transient or elevated levels that are not captured in static measurements. Consequently, LF-EL and LF-MF exposure values should be interpreted as baseline estimates and may underestimate real-world occupational exposure. Such underestimation could, in principle, lead to an overestimation of the strength of associations between low-frequency exposure components and sleep outcomes. However, given that the observed associations were negative and not statistically significant, this potential bias is unlikely to have meaningfully affected the estimated effect sizes for the EMF exposure mixture and HF-EF.

Residential EMF exposure was assessed semi-quantitatively, based on the questionnaire co-developed with the Federal Office for the Environment and dichotomized for stratification purposes and exposure values derived from the literature. The lack of objective measurements, in bus drivers' homes precludes validation of the residential exposure index and assessment of potential misclassification. Therefore, the findings from stratified group-separated analyses should be interpreted with caution and should be confirmed in future studies using quantitative, individual measurement-based exposure assessment.

Additional individual-level factors could affect sleep quality and their role in the observed associations between occupational EMF exposure and sleep outcomes would deserve further investigation. This includes the health status of the bus driver's spouse or partner, the presence of babies and small children in the household and their health status, but also lifestyle-related factors such as excessive consumption of coffee and other caffeine-containing drinks, exercising or playing video games before bedtime, alcohol consumption, and eating spicy foods (e.g., chili pepper). Some of them (i.e., lifestyle related factors and presence of small children) have been assessed in the TRAPHEAC, others not. Since these factors are neither associated with bus drivers' occupational EMF exposure, nor situated in the causal pathway between this exposure and the sleep outcomes, we believe that the associations observed in this study are not confounded by any of them. However, each of these factors may act as effect modifier, similarly to (co)exposures and it would be useful to test their effect in a larger study by adding an interaction term in the exposure-response model.

Finally, the absence of residential conditions including noise and lighting is another limitation to mention. Residential noise is a well-established determinant of sleep quality, with chronic exposure to traffic, aircraft, or neighbourhood noise shown to increase sleep fragmentation, prolong sleep latency, and reduce subjective sleep satisfaction (Basner et al., 2011; Muzet, 2007). In our study, the residential noise and light may confound or modify the observed associations between occupational EMF exposure and sleep outcomes. However, given that our cohort is composed of professional bus drivers with highly variable work schedules and exposure patterns, the dominant sources of sleep disruption are likely occupational and schedule-related, suggesting that the lack of residential noise and light measurements may attenuate but is unlikely to fully obscure the occupational EMF effects observed.

5. Conclusion

In conclusion, using a dual methodological approach combining linear regression and Bayesian Kernel Machine Regression, this study nested within the TRAPHEAC cohort of Swiss bus drivers showed that occupational HF-EF exposure is positively associated with poorer sleep outcomes, including global sleep quality, insomnia, and excessive daytime sleepiness. These associations were consistently observed both for HF-EF specifically and for the combined mixture of HF-EF, LF-EF, and LF-MF exposures, and remained robust to adjustment for sex, age, intensity of nightshift work, and occupational noise exposure as well as to the exclusion of participants exposed to high ambient temperature. However, the BKMR dose-response trends were not statistically significant. Stronger exposure–response gradients in individuals with low residential EMF exposure highlight the modifying effect of non-occupational sources, whereas attenuation in highly exposed individuals suggests a saturation or masking phenomenon, emphasizing the importance of considering both cumulative and mixed-source EMF exposures in occupational sleep health assessments. As the study sample was small and several individual-level factors that may affect sleep quality were unavailable for assessing their influence on the observed associations, future research is warranted to confirm these findings and address these limitations.

Ethics approval and consent to participate

The study was approved by the Swiss ethical commission represented by the Committee of Vaud Canton (Decision Ref CER-VD, 2023-02105 of the 8.8.2024). Each enrolled participant provided the informed electronically signed consent after receiving detailed information about the study protocol and participation modalities.

Consent for publication

Provided as part of the consent to participate.

Availability of data and material

All results are provided in the supplementary materials.

Use of artificial intelligence

ChatGPT-4o and DeepL Pro were used to support English grammar verification and correction during the preparation of this manuscript.

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CRediT authorship contribution statement

Matej Soumillion: Formal analysis, Methodology, Visualization, Writing – original draft. **Viviane Fiona Mathilde Remy:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Dusan Petrovic:** Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **J. Hugo Dil:** Conceptualization, Methodology, Validation, Writing – review & editing. **Irina Guseva Canu:** Conceptualization, Funding acquisition, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing.

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Appendix A. Supplementary data

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