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Intersectional sleep disparities: association between multiple social intersections, perceived neighborhood deprivation, and sleep disturbance in Europe

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Abstract

The prevalence of sleep disturbance, related with social status and privilege, is unevenly distributed within societies. Individual social determinants that are embedded within broader neighborhood contexts intersect and jointly shape sleep disparities. This study incorporates a quantitative intersectional framework to better understand the structural inequalities in sleep disturbance for older adults, focusing on the social–ecological model of sleep and how individual and social context factors interact. Our sample consisted of 17 035 individuals aged 50+ from waves 4 and 5 of the Survey of Health, Aging and Retirement in Europe (SHARE). We created 72 unique intersectional strata by interacting individual axes of social inequality (sex/gender, family caregiving, education, occupation) with perceived neighborhood deprivation. To investigate the variations in sleep disturbance across intersectional strata, we employed intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA). Intersectional strata explained a fair magnitude of the variance in sleep disturbance (6.3%). The most disadvantaged groups, particularly women with low education, low-skill occupations who were caregivers in perceived highly-deprived neighborhoods, exhibited the largest number of sleep disturbance. Sex/gender and perceived neighborhood deprivation were the main predictors of such differences. While some multiplicative effects were found, additive effects predominated. Given the importance of sleep for health, coupled with increasing social inequalities, our findings suggest that intersectionality is a valuable framework for mapping and addressing sleep disparities. Tailored interventions should go beyond individual factors to include community-level measures, targeting socially vulnerable groups, especially women experiencing neighborhood deprivation.

Introduction

Sleep disturbance, including disruptions in quality, timing, and duration, is associated with psychiatric symptomatology, cardiovascular disease, metabolic syndrome, and increased mortality [1–4]. Although disturbed sleep is increasingly prevalent among older European adults [5], it remains under-researched and underprioritized in public health interventions [6]. Most sleep research focuses on biological determinants, yet social and environmental factors are equally critical [7]. Social epidemiology of sleep has unraveled how social determinants like sex/gender, education, or occupation predict sleep disturbance [8], while the social–ecological model of sleep health recognizes how broader social–environmental settings like neighborhood deprivation interact to affect sleep disturbance [9].

The social–ecological model of sleep health provides a comprehensive approach for understanding how individual, social, and societal factors collectively shape sleep [9]. Individual factors (e.g. SES, behaviors) exist within social contexts (e.g. family, neighborhood), and these within broader societal contexts (e.g. discrimination, economy) (Supplementary Fig. S1). These interconnected levels interact with environmental factors (e.g. perceived neighborhood safety) influencing individual behaviors and vice versa, which underscores the importance of examining sleep social determinants beyond the individual level [1]. The social and physical environment, and particularly neighborhoods, generate and perpetuate sleep disparities through social (e.g. norms), psychological (e.g. perceived safety, discrimination), and physical factors (e.g. pollution, access to services). Intersectionality theory posits how structural inequalities and systems of power/oppression uniquely affect individuals at the intersections of their social characteristics [10]. In this regard, intersectionality theory suggests that structural forces shape neighborhood perceptions, further affecting vulnerability to sleep risks [11, 12]. Likewise, research revealed that perceived neighborhood characteristics often have stronger associations with sleep than objective measures [13, 14]. While traditional interventions focus on individual factors like

medication, therapy, or sleep hygiene, addressing contextual and structural determinants is crucial for developing public health strategies that promote sleep equity [1].

Within and across neighborhoods, individuals at the intersection of multiple disadvantaged social positions are more likely to experience sleep disturbance due to continuous exposure to discrimination, financial insecurity, or unsafe social environments [15]. Following the PROGRESS-Plus framework [16, 17], we identified particular socio-demographic characteristics that stratify sleep health opportunities and outcomes: sex/gender, family caregiving, education, occupation, and place of residence. Notably, women experience more sleep disturbance than men, and besides physiological differences, this is due to traditional gender norms that prioritize caregiving and household duties over sleep [18, 19]. Likewise, factors such as family duties can impact sleep timing and quality, with more sleep disturbance reported by family caregivers [20]. Furthermore, lower SES (i.e. education, occupation) is linked to more sleep disturbance due to less sleep health literacy, limited access to restful working conditions, and pressures of low-skill jobs like night shifts [2, 21]. Beyond individual characteristics, perceived neighborhood deprivation is associated with more sleep disturbance, reinforcing geographical inequalities in sleep quality [11, 13]. Perceived neighborhood contexts affect sleep through stress, physiological responses, and social engagement [11, 14]. Accordingly, urbanicity is associated with factors (noise, deprivation) that may result in sleep disturbance [13]. Overall, the interconnectedness of social determinants of sleep highlights the need for an intersectional approach [22, 23]. Yet, most studies have examined these factors separately, limiting the understanding of how intersectional sleep disparities emerge.

While scholars advocate the use of intersectionality to advance the understanding of sleep disparities across social subgroups [22, 23], quantitative sleep research rarely incorporated intersectional approaches. Intersectional multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) is a novel, intersectionality-based quantitative method for studying health disparities [24]. MAIHDA models health outcomes by nesting individuals within social strata, defined by unique intersections of socio-demographic characteristics. Compared to traditional multilevel models with interactions, MAIHDA offers advantages in scalability, parsimony, and handling small subgroup samples [25]. Unlike other models, MAIHDA frames intersecting social determinants (e.g. gender, SES) as indicators of systemic oppression (e.g. sexism, classism), addressing the structural roots of sleep disparities [22, 23]. However, sleep outcomes remain unexplored using this framework.

The current study addresses the limited evidence on intersectional sleep disparities within neighborhood-level contexts by integrating an intersectional lens into the social–ecological model of sleep, to study social determinants of sleep disturbance. We aim to map disparities in sleep disturbance across intersectional strata, assess the relative impact of perceived neighborhood deprivation on these disparities, and identify strata experiencing intersectional interaction effects.

Methods

Data and sample

We used data from waves 4 and 5 of the Survey of Health, Aging and Retirement in Europe (SHARE), the largest European panel study with information on demographic, socioeconomic, and health outcomes for people aged 50+ [26]. SHARE data are collected with computer-assisted personal interviews (CAPIs), and the survey has been extensively described elsewhere [26]. Wave 4 (2011) is the latest wave including multiple sleep variables, while wave 5 (2013) collected information on perceived neighborhood context. Of the 38 296 respondents aged 50+ participating in both waves, we excluded: (a) 707 respondents (1.85%) with missing family caregiving information; (b) 486 respondents (1.27%) with missing education information; (c) 5308 respondents (13.87%) with missing occupation information; (d) 13 296 respondents (34.74%) with missing perceived neighborhood context information; (e) 1075 respondents (2.81%) who changed place of residence between wave 4 and wave 5; and (f) 389 respondents (1.02%) missing a sleep variable. The final sample consisted of $N = 17\,035$ (Supplementary Table S1).

Measures

Outcome variable

Our outcome variable was a sleep disturbance index (SDI), a previously used composite score based on two self-reported sleep items in wave 4 [4]. The items captured sleep quality "for the past six months at least" through the questions "Have you been bothered by sleep problems?" and "Have you had trouble sleeping or a change in sleep pattern?". Both were coded as Yes/No. Since internal consistency as a measure of reliability was acceptable (Cronbach's $\alpha = .76$) (Supplementary Table S2), we calculated the index by adding the total number of sleep disturbance (SDI range 0–2).

Main exposure

We defined intersectional strata with individual-level and neighborhood-level factors associated to sleep disturbance: sex/gender (G), family caregiving (F), education (E), occupation (O), and perceived neighborhood deprivation (N). The variable selection was informed by the PROGRESS-Plus framework [17]. The unique combinations of all possible categories resulted in 72 intersectional strata ($[2G] \times [2F] \times [3E] \times [2O] \times [3N] = 72$) [24]. We adopted the approach proposed by Evans27, where contextual-level variables are interacted with individual-level variables to create intersectional strata. Hence, we allowed the effect of perceived neighborhood deprivation to be unique for each combination of individual determinants, modeling the contextual social process of intersectional sleep disparities. More than 73% of the 72 strata consisted of at least 30 observations, indicating a sufficient sample size (Supplementary Table S3) [25].

Sex/gender was coded as women or men, reflecting the binary options provided for sex in SHARE. Acknowledging the limitations of a binary categorization, we opted for the term sex/gender to recognize the conflation of sex and gender in a single survey item. Family caregiving was coded as No/Yes after the question "During the last 12 months, is there someone living in your household whom you have helped regularly with personal care?". Education was assessed following the ISCED-1997, categorizing it into high (5–6), medium (3–4), or low (0–2). Occupation was obtained from the present or latest-held work positions, and coded into two major groups according to ISCO-88: high-skill (HS) or low-skill (LS) occupations.

Perceived neighborhood deprivation was derived from questions on the local area (everywhere within a 20-min walk or a kilometer from home), where participants were asked on their agreement with the following: "vandalism or crime is not a big problem in this area", "this area is kept very clean", "I really feel part of this area", and "If I were in trouble, there are people in this area who would help me". Answers were dichotomized as agree (strongly agree or agree) or disagree (disagree or strongly disagree), reverse coded and aggregated in a single variable (values 0–4, with higher scores indicating more deprivation). Our final variable was coded as low deprivation (0–1), medium deprivation (2–3), or high deprivation (4), aligned with previous studies [27]. Since neighborhood deprivation was only available in wave 5, contrary to all other variables measured in wave 4, we only included participants who did not change place of residence between wave 4 and wave 5.

Statistical analysis

Several studies integrated social–contextual aspects of intersectionality in four key ways: (i) interacting contextual-level variables with

axes of social position [28]; (ii) eco-intersectional multilevel (EIM) modeling with areas of residence nested within intersectional strata [29]; (iii) multilevel models with individuals nested within area of residence [30]; and (iv) cross-classifying intersectional social strata with contextual variables [31]. Approaches (ii), (iii), and (iv) use objective contextual measures; however, since we focus on perceived neighborhood deprivation and its importance for sleep disparities [14], we adopted approach (i).

We used the intersectional MAIHDA framework, which is based on multilevel models where individuals are classified within intersectional strata: individuals were placed at level 1, nested within intersectional strata at level 2 [24]. Recent publications have described the MAIHDA method thoroughly, while providing an overview of its advantages compared to traditional multilevel models with interactions [24, 32]. We applied restricted maximum likelihood (REML) estimation to fit linear multilevel models.

First, we fitted an unadjusted null model (Model 1) to map sleep health disparities across intersectional strata. This model allowed us to calculate the variance partition coefficient (VPC)—equivalent to the intraclass correlation coefficient (ICC)—a measure of discriminatory accuracy reflecting the between-strata variance of sleep disturbance [32]. MAIHDA literature suggests the following VPC classification for discriminatory accuracy: nonexistent (0–1), poor (>1 to ≤5), fair (>5 to ≤10), good (>10 to ≤20), very good (>20 to ≤30), and excellent (>30) [32]. Second, we fitted partially adjusted models (Models 2a–2e) by including one strata-defining variable as fixed effect in each sequential model at a time. In addition to the VPC, we calculated the proportional change in variance (PCV) in each model, which indicates the proportion of between-strata variance explained by the added main effects [32]. Every PCV reflects the extent in which each strata-defining variable (i.e. intersectional dimensions) contribute to the variance of sleep disturbance. Finally, we fitted a fully adjusted model (Model 3), which displays the contribution of each strata-defining variable to the joint effect on average. The VPC illustrates the remaining between-strata variance after adding all main effects. The PCV reflects the variance explained by main effects only (additive effects), hence 1-PCV represents the unexplained variance due to intersectional interactions (multiplicative effects). We included country dummies to control for cross-country variation, although prior studies with the same data showed that country differences explained little variance in sleep disturbance (Supplementary Table S5 and Fig. S2) [33].

Based on Model 3, we calculated the predicted sleep disturbance and strata-level residuals for each stratum, the later indicating potential interaction effects for each of the intersectional strata (higher or lower sleep disturbance than expected from the main effects only) [32]. Finally, given the association of urbanicity and sleep disturbance for groups aged 66+ [34], we performed a sensitivity analysis by controlling for urbanicity (rural/urban living area) in Model 4. All analyses were conducted with Stata/BE®18.0, where statistical significance was assessed by 95% confidence intervals not including zero.

Results

The average age of the sample was 64.4 years old, with just over half of participants being female (Table 1). A minority of the sample undertook regular family caregiving on adults (8.0%), whereas most respondents had medium or low education. Almost two-thirds of participants had a high-skill occupation. Most individuals perceived medium or low neighborhood deprivation, whereas 20.5% perceived high neighborhood deprivation. About two-thirds of respondents lived in urban areas. One-third of the sample reported having trouble sleeping, while 22.4% reported recent sleep complaints. A large share (37.0%) of study participants reported at least one type of sleep disturbance occurring recently.

Highly vulnerable intersectional strata, such as women with caregiving duties and low SES, had the highest sleep disturbance on average (Fig. 1). Particularly, individuals with the same social characteristics exhibited between-neighborhood sleep disparities, with high-deprived neighborhoods entailing higher sleep disturbance. The stratum comprising women undertaking family caregiving, with medium education, low-skill occupation, and living in high-deprived neighborhoods had the highest sleep disturbance (SDI = 1.0). This implies a three-fold difference compared to the stratum with the least sleep disturbance (SDI = 0.3), comprised by men not undertaking family caregiving, with high education, high-skill occupation, and living in low-deprived neighborhoods.

Table 1. Descriptive statistics of the study sample[a]

Variable	*N*	%
Total	17 035	
Age (mean ± SD)	64.4 (9.3)	
Sex/gender		
Male	7859	46.1
Female	9176	53.9
Family caregiving		
No	15 670	92.0
Yes	1365	8.0
Education		
High	4119	24.2
Medium	6933	40.7
Low	5983	35.1
Occupation		
High-skill occupation	10 580	62.1
Low-skill occupation	6455	37.9
Perceived neighborhood deprivation		
Low deprivation	4760	27.9
Medium deprivation	8791	51.6
High deprivation	3484	20.5
Living area		
Urban	10 791	63.7
Rural	6147	36.3
Sleep outcomes		
Sleep complaints past 6 months	3816	22.4
Trouble sleeping/change in pattern	5860	34.4
Sleep disturbance index (mean ± SD)	0.6 (0.8)	

a: The sleep disturbance index (SDI) takes values between 0 and 2; SD: standard deviation.

The VPC of the null model (Model 1) indicated that 6.3% of the variance in sleep disturbance was attributable to the intersectional strata (Table 2). This implies a good level of discriminatory accuracy [32]. In the partially adjusted models (Models 2a–2e), the PCVs revealed that sex/gender (77.2%) and perceived neighborhood deprivation (40.3%) were the largest contributors to differences in sleep disturbance across strata. In contrast, family caregiving (11.4%), education (6.1%), and occupation (1.8%) had a lower contribution. The fully adjusted model (Model 3) showed that, on average, women experienced more sleep disturbance than men, as did people undertaking family caregiving compared to those who did not. Individuals with lower education reported higher sleep disturbance than their medium and high education counterparts, while those in low-skill occupations had more sleep disturbance than their high-skill counterparts. High perceived neighborhood deprivation was significantly associated with more sleep disparities, compared to medium and low perceived deprivation.

The VPC in Model 3 indicated that after adjusting for main effects, only 0.6% of the between-strata variance remained. A PCV of 90.9% revealed that the majority of intersectional variance in sleep disturbance was explained by additive effects, whereas the remaining variance (9.1%) was due to multiplicative effects (i.e. intersectional interactions). Likewise, the residual analysis revealed that only seven strata exhibited significant multiplicative effects (Fig. 2 and Supplementary Table S4). Four of them had higher sleep disturbance than expected from the additive effects only—CIs above 0 indicating

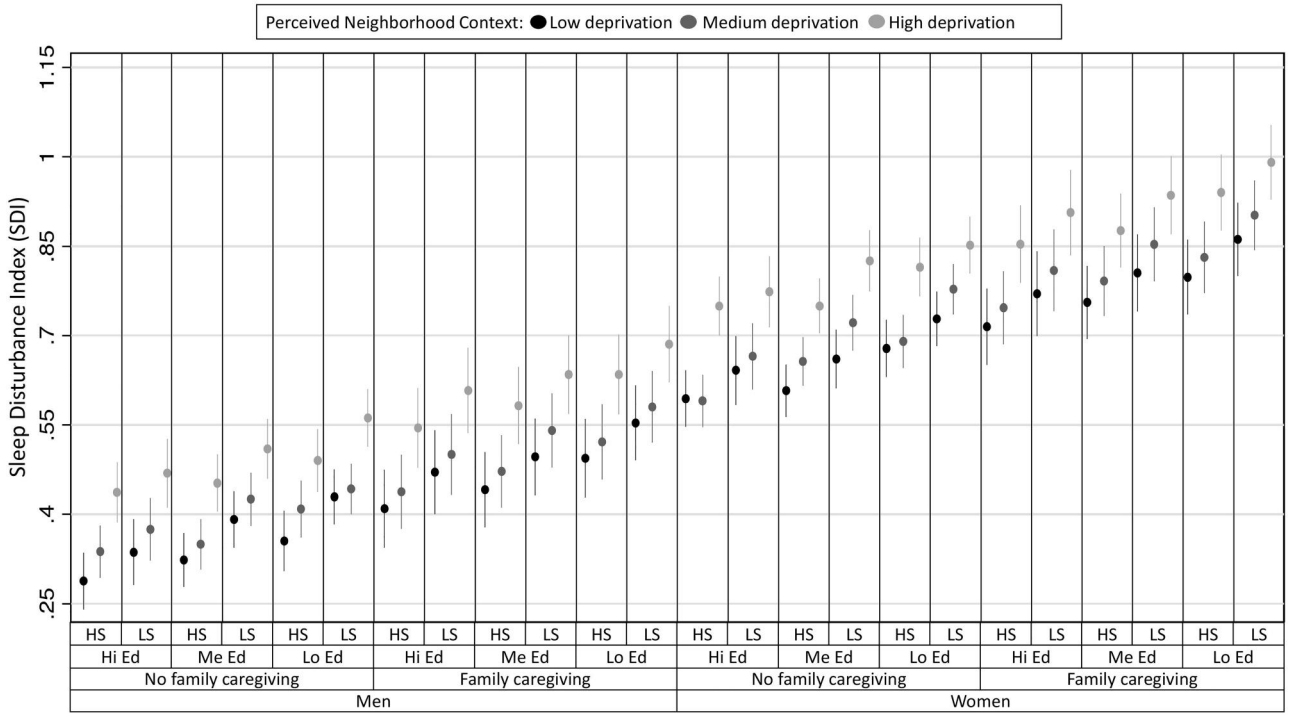

Figure 1. Predicted sleep disturbance for each intersectional social stratum, with point estimates and 95% confidence intervals obtained from MAIHDA Model 3 ($N = 17\,035$). The grey colour-scheme indicates perceived neighborhood context. Higher SDI means more sleep disturbance. Abbreviations: HS = high-skill occupation; LS = lLow-skill occupation; Hi Ed = high education; Me Ed = medium education.

Table 2. Intersectional MAIHDA models on the sleep disturbance index ($n = 17\,035$)[a]

Coefficient (95% CI)	Model 1	Model 2a	Model 2b	Model 2c	Model 2d	Model 2e	Model 3
Constant	0.6 (0.5, 0.7)	0.4 (0.4, 0.5)	0.5 (0.5, 0.6)	0.5 (0.4, 0.6)	0.6 (0.5, 0.7)	0.4 (0.4, 0.6)	0.3 (0.2, 0.3)
Sex/gender							
Male		Ref.					Ref.
Female		0.3 (0.3, 0.4)					0.3 (0.3, 0.3)
Family caregiving							
No family caregiving			Ref.				Ref.
Family caregiving			0.1 (0, 0.2)				0.1 (0.1, 0.2)
Education							
High education				Ref.			Ref.
Mid education				0.1 (−0.1, 0.2)			0.1 (0.0, 0.1)
Low education				0.2 (0.0, 0.3)			0.2 (0.1, 0.3)
Occupation							
High-skill					Ref.		Ref.
Low-skill					0.0 (−0.1, 0.1)		0.1 (0.0, 0.1)
Perceived neighborhood							
Low deprivation						Ref.	Ref.
Medium deprivation						0.1 (−0.1, 0.2)	0.1 (0.0, 0.1)
High deprivation						0.3 (0.0, 0.3)	0.2 (0.1, 0.3)
Random effects							
Between-strata variance (95% CI)	0.04 (0.03, 0.06)	0.01 (0.01, 0.02)	0.04 (0.02, 0.06)	0.04 (0.02, 0.06)	0.04 (0.03, 0.06)	0.02 (0.01, 0.04)	0.01 (0.00, 0.01)
VPC (%)	6.3%	1.5%	5.6%	5.9%	6.3%	2.6%	0.6%
PCV (%)	–	77.2%	11.4%	6.1%	1.8%	40.3%	90.9%

a: Model 3 controls for country dummies; CI = confidence interval; VPC = variance partition coefficient; PCV = proportional change in variance. Coefficients with 95% CI not including zero were considered statistically significant.

a hazardous effect, whereas three strata had lower sleep disturbance than expected—CIs below 0 indicating protective effect. According to these residuals, the combination of high SES (high education and high-skill occupation) with mid/high perceived neighborhood deprivation amplified the risk for sleep disturbance through intersectional interactions, as these strata showed multiplicative hazardous effects. Conversely, intersectional protective effects for sleep disturbance were evident for strata with mid/low neighborhood deprivation, combined with a mixed pattern of higher and lower SES. Finally, the sensitivity analysis revealed that urbanicity was not significantly associated with sleep disturbance, with additive effects explaining a larger part of the between-strata variance (Supplementary Table S5).

Discussion

In this study, we explored inequalities in sleep disturbance across intersectional strata, focusing on differences in perceived neighborhood deprivation. Using a European sample of older adults and intersectional MAIHDA, we found significant differences in sleep disturbance across strata, primarily explained by additive rather than

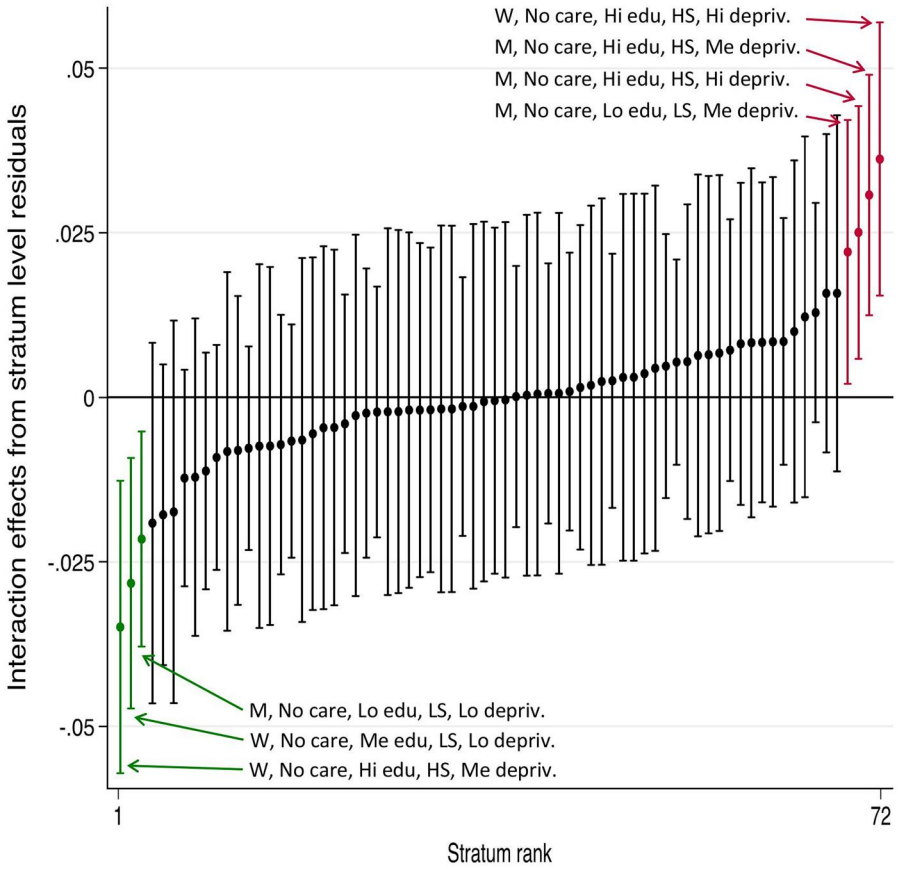

Figure 2. Strata-level residuals obtained from MAIHDA Model 3 for each intersectional stratum, and their 95% confidence intervals (CIs). Intersectional strata are ranked from lowest to highest residual. A residual of zero (horizontal line) equals to the expected value based on main effects only, thus strata with 95% CI above (below) zero displayed multiplicative hazardous (protective) effects, colored in red (green). Abbreviations: M = men; W = women; Hi edu = high education; Me edu = medium education; Lo Edu = low education; HS = high-skill occupation; LS = low-skill occupation; Hi depriv. = high neighborhood deprivation; Me depriv = medium neighborhood deprivation; Lo depriv. = low neighborhood deprivation.

multiplicative effects. Sex/gender and perceived neighborhood deprivation contributed the most to these differences, followed by family caregiving duties. Notably, individuals with high SES and mid/high neighborhood deprivation experienced the intersectional hazardous effects. Our findings highlight how the intersection of social determinants influences sleep disparities, which reflect broader intersecting inequalities beyond individual factors.

Our results revealed that 37.0% of the sample reported at least one recent sleep disturbance, highlighting a significant public health issue among European older adults [5]. Consistent with previous research, we found that factors such as being a woman, family caregiving, low education, low-skill occupations, and perceiving the neighborhood as deprived were associated with higher sleep disturbance [6, 8, 35]. These factors contribute to sleep disturbance through stressors like financial insecurity, daily discrimination, less sleep health literacy, and conflictive work–life balances [36]. Noticeably, the combination of these determinants led to higher sleep disturbance, with multiple social intersections and perceived neighborhood deprivation jointly creating intersectional sleep disparities. While between-strata differences were mostly additive, our findings reflect that broader social forces, including systems of power and oppression, contribute to sleep disparities [23].

Perceived neighborhood deprivation largely contributed to the risk of sleep disturbance compared to individual determinants. Additionally, strata with high SES but high perceived neighborhood deprivation had hazardous intersectional effects, whereas some with low neighborhood deprivation had protective intersectional effects. Our results indicate that a safe and cohesive environment might buffer the effects of disadvantaged social identities. This highlights the importance of placing intersectional sleep inequalities [37], since the same social position may influence sleep differently depending on the context [28]. These findings are in line with prior work revealing that cohesive and safe environments contribute to less sleep disturbance [13], whereas non-cohesive and deprived areas are associated with worse sleep outcomes [35]. Neighborhood contexts can influence sleep through psychosocial, physiological, and social engagement mechanisms [11]. Perceived low social cohesion, dirtiness, and crime may create stress and anxiety, while increasing allostatic load and inflammatory biomarkers, which contribute to sleep disturbance [31, 38]. Conversely, area belonging or community support improves sleep outcomes through shared resources, care access, or reinforcement of social norms and behaviors. These situations create opportunities for restful sleep, with a greater perception of safety allowing for relaxation, whereas high perceived deprivation jeopardizes such behaviors and prevents better sleep outcomes. Social environments shape daily routines, interacting with stressors and thereby increasing the risk of sleep disturbance. Our application of the social–ecological framework shows that interacting individual and social factors critically influence sleep disturbance, amplifying structural disparities in deprived neighborhoods.

The present study reinforces the importance of social determinants of sleep [7], since individuals in more advantaged social positions (men, no family caregiving, high SES) reported less sleep disturbance. Likewise, disadvantageous social positions are linked to institutionalized oppression and structural discrimination, reproducing intersectional social inequalities onto sleep disparities. It is imperative not to take for granted the privilege of access to comfort, safety, and privacy, which are essential for good sleep, as suggested

by the few studies applying intersectional MAIHDA with neighborhood-level contexts [28, 31]. MAIHDA proves as a useful methodology to unravel how broader social contexts matter for different intersectional subgroups in creating sleep and health disparities. In societies with rising inequality, this underscores the need for intersectionality-informed strategies to identify and support subgroups at higher risk of sleep disturbance [39].

Perspectives and implications

The promotion of good sleep is an overlooked public health opportunity especially in older adults, considering its relation with numerous health outcomes and the modifiable nature of certain social determinants [1]. We found a complex pattern linking multiple social inequalities and their intersections to sleep disparities. Notably, people in the same social position reported varying sleep disturbance depending on their perceived neighborhood deprivation. This emphasizes the need to integrate social contexts in quantitative intersectional analyses of health inequalities, as place shapes the complexity of lived experiences within population subgroups [37]. Future research on sleep disparities should incorporate an intersectional lens and consider broader social factors that are beyond the scope of individuals, while still affecting their sleep.

Our results suggest that individual sleep interventions, particularly for women with caregiving duties and low SES, could be less effective unless environmental factors were included. It is crucial to shift the focus from individuals as the only agency factor to, instead, investigating the implications of neighborhood-level sleep prevention approaches [23, 40]. In combination with individual-level sleep behavioral recommendations or therapy, targeted sleep promotion interventions should be placed at multiple contextual levels, for instance well-maintained neighborhoods, area-specific equitable access to resources, and sleep-friendly media and workplaces. Echoing recent calls for action in disadvantaged neighborhoods [40], MAIHDA could serve as a tool to develop targeted interventions in "sleep deserts", where structural discrimination requires culturally tailored interventions at the community level. Based on the social–ecological model of sleep, we encourage the prioritization of context and connection over individualism in public health programs with the aim to promote sleep health equity.

Strengths and limitations

We used a large, representative sample with validated scales, enabling results generalization. The social–ecological model of sleep health guided our design, providing insights into multilevel socio-environmental determinants of sleep. We also applied intersectionality theory through MAIHDA modeling to address how intersections of social determinants jointly contribute to sleep disparities. A limitation was self-reported sleep disturbances, as objective measures like polysomnography or accelerometers were unavailable in SHARE. Future research should combine subjective and objective sleep evaluations for more comprehensive insights. Neighborhood context was also self-reported, lacking geographical data for objective deprivation measures. While subjective neighborhood assessments are valid predictors of sleep, future studies should integrate objective area deprivation data with intersectionality. Additionally, SHARE lacks race/ethnicity and sexual identity indicators, critical factors in US studies on sleep disparities among vulnerable groups. We excluded migration background given its limited operationalization, which could not adequately capture racial/ethnic dimensions. Hence, European studies should incorporate race/ethnicity and sexual identity data to better understand the intersectionality of sleep disparities. Lastly, our sample included only older adults aged 50+, a group prone to sleep disturbances and cumulative social inequalities. Future research should examine intersectional sleep disparities in younger cohorts.

In conclusion, using an intersectional lens is crucial to identify sleep and health disparities and inform precision public health measures. Given the importance of neighborhood factors, future research should integrate broader contexts and focus on multilevel sleep promotion interventions addressing factors beyond the individual.

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Author contributions

E.A.P., P.G., and J.L.O.S. conceptualized the research idea and E.A.P. wrote the original article. E.A.P. carried out the initial data analysis, with input from P.G. and J.L.O.S. X.D. and J.L.O.S. critically revised the article and analyses. P.G. acquired the funding to obtain financial support for this publication. All authors approved the final article.

Supplementary data

Supplementary data are available at *EURPUB* online.

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Data availability

This study uses data of the Survey of Health, Ageing, and Retirement in Europe (SHARE). SHARE data are publicly available upon free registration (https://share-eric.eu/data/, accessed on 21 September 2024).

Key points

- There were substantial sleep disparities across intersectional groups.
- Sex/gender and perceived neighborhood deprivation were key drivers of sleep disparities.
- Perceived neighborhood deprivation was linked to sleep disturbance regardless of individual social determinants.
- The use of an intersectional lens through MAIHDA is crucial to shape public health policies.
- Multilevel targeted sleep promotion interventions should consider broader social contexts.

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