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The effect of urban greenspace on adolescent sleep patterns

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ABSTRACT

We investigated the effects of long-term greenspace deprivation on sleep during adolescence. Using data from a UK birth cohort, we studied deviations from age-recommended sleep duration through Time Use Diaries. Our sample ($N = 1370$; 53% female) of urban adolescents had been exposed to the same levels of neighbourhood greenspace from birth up to age 14 years when their time use was tracked. We factored in sex and ethnicity, family income, long-term illness, sharing of a bedroom, access to a garden, as well as air pollution and perceived area safety. Even after full adjustment, there was a significant interaction between greenspace availability and income when predicting sleep duration, such that low-income adolescents living in the greyest urban areas were found to sleep more than the 8–10 h recommended for their age group, while the inverse was true for their counterparts living in areas with more greenspace.

KEYWORDS
Greenspace; sleep; adolescence; urban; environment; pollution

Introduction

Sleep is an essential component of healthy physiology and mental well-being, and the sleep patterns of children and adolescents have been examined in detail in recent years. There is substantial evidence showing a marked decline in sufficient sleep duration in adolescents in England (Brooks, Klemera, Chester, Magnusson, & Spencer, 2020), the United States (Keyes, Maslowsky, Hamilton, & Schulenberg, 2015), Finland (Kronholm et al., 2015), Norway (Hysing, Harvey, Linton, Askeland, & Sivertsen, 2016), and elsewhere (Matricciani, Olds, & Petkov, 2012), although cross-cultural differences (Cheung, Takemura, Ou, Gale, & Heine, 2021) have a significant impact on trends across different regions (Gradisar, Gardner, & Dohnt, 2011). Deviations from the recommended sleep range duration in childhood and adolescence can affect academic performance (Sharman & Illingworth, 2020), mental health (Zhang et al., 2017), a wide range of outcomes across cognition and psychosocial function, but also cardiometabolism, adiposity and musculoskeletal pain (Matricciani, Paquet, Galland, Short, & Olds, 2019). During adolescence, in particular, increasing pressures in socio-educational environments can impact good sleep hygiene through stress (Pine, Liu, Abitante, Sutherland, & Garber, 2022) and coping self-efficacy (Brink, Lee, Manber, Yeager, & Gross, 2021). Modern lifestyles, such as sedentary behaviours and exposure to evening light and excessive screen time, have also been implicated in this (Bartel, Gradisar, & Williamson, 2015). The resulting sharp increase in sleep variability during early-to-middle

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adolescence has been associated with disruptions in brain maturation (Galván, 2020) and lower white matter integrity, in contrast with what is developmentally expected for this age group (Telzer, Goldenberg, Fuligni, Lieberman, & Gálvan, 2015).

To date, numerous biological, physiological, psychological and socio-economic factors have been studied in relation to paediatric sleep (Marco, Wolfson, Sparling, & Azuaje, 2011). However, the role of neighbourhood ecology and the built environment, much examined in relation to adult sleep, has been largely ignored. For example, ambient air pollution has been associated with poorer sleep in adults, possibly via obstructive sleep apnoea (Billings et al., 2019). Conversely, availability of area greenspace has been related to better sleep patterns in adult populations (Astell-Burt, Feng, & Kolt, 2013), and nature exposure has been shown to predict better sleep in these populations (Shin, Parab, An, & Grigsby-Toussaint, 2020). In children, by contrast, the role of greenspace has only been examined in one study using parent-reported sleep duration (Feng et al., 2020). A recent systematic review of the role of the built environment in children's sleep (Mayne, Mitchell, Virudachalam, Fiks, & Williamson, 2021) concluded that the role of greenspace and other neighbourhood physical environment exposures has been much neglected and must be a research priority. This neglect is surprising because exposure to nature and residential greenspace during childhood has been associated with better mental health outcomes during childhood and adolescence and into adulthood (Engemann et al., 2019), possibly in a dose-response manner (Feng & Astell-Burt, 2017; Shanahan et al., 2016). Although the exact mechanisms remain largely unknown, both psychological and physiological pathways could be at play (Hartig, Mitchell, De Vries, & Frumkin, 2014), and greenness may be improving health outcomes by reducing stress (Wells & Evans, 2003) and promoting physical activity and social contact, while mitigating air pollution, noise, and heat exposure (James, Banay, Hart, & Laden, 2015). It may also directly impact on cognitive functioning. In dense urban environments, for example, the relative lack of greenness and increased levels of traffic (noise and air pollution) appear to adversely affect brain maturation in the functional domain (Pujol et al., 2016).

In the present work we address this gap by investigating the impact of greenspace availability and neighbourhood ecology on the sleep patterns of 14-year-old adolescents. Using data from the UK's Millennium Cohort Study (MCS), a large population-based longitudinal birth cohort, we ask whether the quantity of greenspace in urban areas [i.e. denser settlements with populations of over 10 000 (Bibby & Shepherd, 2004)] could predict deviations from the recommended sleep duration range for adolescents at around 14 years of age: 8–10 h of sleep per day, in total, on a regular basis (Paruthi et al., 2016). This is the recommended sleep duration range for adolescents from the age of 13 (and up to around 18 years of age), a range which is associated with improved attention and behaviour, learning, memory, emotion regulation, and overall mental and physical health. Insufficient adolescent sleep on the other hand is associated with several negative outcomes, including increased risk of self-harm, suicidal thoughts, and suicide attempts (Paruthi et al., 2016). On the other end of this spectrum, oversleeping is associated with increased risk of mood, anxiety, substance use, and behavioural disorders (Zhang et al., 2017).

The age of approximately 14 years corresponds to the sixth survey wave ('sweep') of the MCS, when detailed 24-h Time Use Diary (TUD) entries were recorded. We hypothesised that greenspace deprivation would be related to deviations from the optimal sleep duration, in line with the evidence provided from adult samples. However, we also expected that this association would be moderated by income, such that the association would be attenuated for those from less socio-economically disadvantaged families who, in general, would be more able to provide the type of housing, family routines, and transportation options associated with better sleep hygiene (Vandendriessche et al., 2022).

Methods

Analytic sample

The MCS follows around 19 000 children born in 2000–2002 (Joshi & Fitzsimons, 2016), from around 9 months (sweep 1) to around 3, 5, 7, 11, 14 and 17 years (sweeps 2–7). The geography of electoral wards provided the sampling frame for MCS, which was designed to over-represent families living in wards of high child poverty across the UK, wards with high proportions of ethnic minorities in England, and the smaller UK countries (Plewis, Calderwood, Hawkes, Hughes, & Joshi, 2004). Most of the information was collected through interviews with, and self-completion questionnaires from, the main respondent (overwhelmingly the mother) in the child's home. Ethical approval was gained from UK Multi-Centre Ethics Committees, and parents gave informed consent before interviews took place, as did the cohort children themselves from age 14 onwards.

At the age 14 sweep, 11 726 families took part in the MCS (11 872 cohort members). Our study's analytic sample includes adolescents (singletons and first-born twins or triplets) who, as at the age 14 sweep, were living in urban areas in the UK and had lived consistently since the beginning of the MCS in a ward in the same decile of neighbourhood greenspace (see Measures). This ensures that our urban adolescent sample had been exposed to the same amount of neighbourhood greenspace since infancy. At the age 14 sweep the cohort members were also asked to complete a Time Use Diary (TUD), which tracked sleep patterns and other daily activities over two days. In total, approximately 4770 cohort members had responded positively and submitted a TUD, but just under a third of them (around 1500) were urban adolescents who had stayed in the same greenspace decile throughout the survey. For our analytic sample selection, we also considered whether a cohort member had any issues filling in the relevant entries of the TUD. As there were two days and each activity spanned multiple timeslots, we excluded cohort members who reported issues in more than half of their entries, which reduced our sample size by around 8% in the weekday analysis. The weekdays analytic sample was therefore 1370 adolescents (53% female), clustered in 263 wards at the beginning of MCS. All had data on neighbourhood greenspace.

Measures

Sleep range, age 14

Cohort members completed a TUD for two days selected at random (one of them was during the weekend). The TUD captures activities in more than 40 categories over two 24-h periods. The data were collected using a 'concurrent mixed-mode approach': online, using an app or on paper. One of the categories was 'Sleeping and resting (including sick in bed)' and it is this activity that we focus on in this study. All activities have start and end times, and the harmonised version of the TUD provides the duration of each activity in timeslots of 10 min. For the sleep activity, we derived a variable for 'total sleep duration' during the 24-h period tracked by the TUD. Comparing the cohort member's sleep duration against the recommended sleep duration for this age group gives us the main variable of sleep range. Therefore, the outcome variable, 'Sleep range', is set equal to 0 as a reference point, and this corresponds to a total sleep duration over a 24-h period of between 8 and 10 h. For each hour less than this recommended range we subtract a unit, while for each hour of oversleeping we add a unit. As a result, 'Sleep range' takes integer values in the interval $[-3, 3]$ where a value of -1 corresponds to insufficient sleep of up to one hour below the recommended range, and $+1$ corresponds to oversleeping by up to one hour above the recommended range. The case of -3 (or $+3$) corresponds to sleeping below (above) this range by 3 h or more.

Neighbourhood greenspace availability ('GSA')

Quantity of neighbourhood (ward) greenspace was one of the domains assessed by the Multiple Environmental Deprivation Index, or 'MEDIx' (CRESH, 2010), an ordered UK-wide measure of physical environment deprivation that represents the balance of pathogenic and salutogenic characteristics in a ward (Richardson, Mitchell, Shortt, Pearce, & Dawson, 2010). The greenspace measure in MEDIx (Richardson & Mitchell, 2010) was estimated by using information from the Coordination of Information on the Environment (CORINE) and the 2001 Generalised Land Use Database (GLUD). In MCS, the percentages of ward-level greenspace have been converted to deciles. In the urban MCS sample at the age 11 sweep, for example, the lowest decile corresponds to wards with less than 19% greenspace and the top to those with more than 80% (Flouri, Papachristou, & Midouhas, 2019). To assess the effect of longitudinal exposure to greenspace on adolescent sleep, we created a dichotomous variable (least exposure to greenspace or not) measuring if, by the age 14 sweep, the child had been living continuously from 9 months old in a ward that was among the lowest 3 deciles of greenspace, in line with previous studies (Flouri et al., 2019). Therefore, our main exposure is greenspace availability (GSA) since infancy, treated here as a dichotomous variable: greenspace deciles 1, 2, 3 correspond to "Grey areas" (or, equivalently, a numeric value of 0), while the rest (deciles 4–10) correspond to "Other areas" (or a numeric value of +1).

Covariates

We adjusted for area, family, and individual covariates. The area-level covariates were air pollution, MCS stratum, and perceived area safety. '*Air pollution'* (ranging from 1 to 10, with 10 being the decile of the most polluted areas) in the neighbourhood (as given in the age 14 sweep) was also derived from the MEDIx using a measure of annual mean concentrations of nitrogen dioxide (NO_2) within each UK ward. Mean values were population-weighted using output area units from 1999 to 2003. Data points were taken from 1 km grids, modelled from the National Atmospheric Emissions Inventory. These were then converted to deciles across all UK wards prior to linking them with MCS (Church & Midouhas, 2016). The neighbourhood social environment was approximated, also at ward-level, by the MCS sampling '*Stratum*' at the beginning of MCS. For each UK country, there was an advantaged and a disadvantaged stratum. In England, there was also an ethnic minority stratum. The '*Ethnic minority'* stratum comprises English wards that had an ethnic minority indicator of at least 30% in the 1991 Census, that is, at least 30% of their total population fell into the two categories 'Black' (Black Caribbean, Black African and Black Other) or 'Asian' (Indian, Pakistani and Bangladeshi). The '*Disadvantaged'* stratum includes wards which were not part of the Ethnic minority stratum, and which fell into the upper quartile (poorest 25% of wards) of the ward-based Child Poverty Index (CPI). Finally, the *'Advantaged'* stratum includes wards which were neither a part of the Ethnic minority stratum nor in the top quartile of the CPI. Lastly, the neighbourhood's safety level ('*Unsafe area'*) as reported by the cohort member's parent at the age 14 sweep was included to control for the role of perceived area safety in the use of public greenspace; its values range from 1 (most safe) to 4 (least safe).

In terms of family characteristics at the age 14 sweep, we controlled for '*Income*', given in OECD equivalised income quintiles for the household, and whether the family had access to a domestic garden or not ('*Access to domestic garden*').

In terms of individual-level covariates, we adjusted for '*Sex*' (male/female), as well as whether at age 14 years the cohort member shared a bedroom or not ('*Shared bedroom*'), or if they had a long-term illness or not ('*Illness*'). We also adjusted for '*Ethnicity*', as reported in the age 14 sweep using the UK Census's 6 large groups: White, Mixed, Indian, Pakistani and Bangladeshi, Black or Black British, or Other Ethnic group (including Chinese, or Other). In the analysis, we also controlled for whether the day of the TUD administration was unusual in some way or not ('*Unusual day*'). Sleep range may have been affected if the day was unusual for some reason (for instance, because the cohort member was sick or because there was a religious event that they participated in).

Analytic strategy

This took place in three steps. First, we examined the impact of sample selection by running a sample bias analysis. Second, we examined the correlations between the main variables. Third, we proceeded with the regression models, with and without a greenspace-income interaction term; missing data in these models were handled by multiple imputation. The regression models were fitted separately for weekends and weekdays. We detail each step below.

Sample bias

Sample bias analysis was performed using survey-weighted descriptive statistics to identify our sample in comparison to the rest of the sweep's cohort. The volume of missing data was also identified at this stage, and this informed the multiple imputation process described later in this subsection.

Correlations between the main variables

The primary variables of interest are the outcome ('Sleep range') and main exposure ('GSA') given in deciles, prior to transforming it into a dichotomous variable. Therefore, correlations were calculated between these two variables, as well as between each of them and family income. We also calculated the mean sleep duration (in hours) against greenspace availability, GSA in deciles, as a bar chart.

Regression models

To examine the link between greenspace exposure ('GSA' as a dichotomous variable) and recommended sleep duration ('Sleep range'), we fitted two linear regression models. The first, minimally adjusted model ('core model 1'), only included (alongside GSA) air pollution ('NO_2'), 'Stratum' and income ('INC'):

$$Sleep\ range = a + b_1 \times GSA + b_2 \times INC + b_3 \times NO2 + b_4 \times Stratum$$

The second, fully adjusted model ('adjusted model 1'), included the other seven covariates, namely, ethnicity, area safety, sex, bedroom sharing status, access to a garden, presence of any chronic illness, and whether the tracked day was unusual or not:

$$\begin{aligned} Sleep\ range = {} & a + b_1 \times GSA + b_2 \times INC + b_3 \times NO2 + b_4 \times Stratum + \ b_5 \times Sex + b_6 \times Ethnicity \\ & + b_7 \times Garden + b_8 \times Bedroom + b_9 \times Illness + b_{10} \times Unsafe\ area + b_{11} \\ & \times Unusual\ Day \end{aligned}$$

To examine the interaction of GSA with income, we added their interaction in the first, minimally adjusted model ('core model 2'):

$$Sleep\ range = a + b_1 \times GSA + b_2 \times INC + b_3 \times NO2 + b_4 \times Stratum + b_{12} \times GSA \times INC$$

Finally, we added to this model all remaining (seven) covariates ('adjusted model 2'):

$$\begin{aligned} Sleep\ range = {} & a + b_1 \times GSA + b_2 \times INC + b_3 \times NO2 + b_4 \times Stratum + b_{12} \times GSA \times INC + \ b_5 \times Sex \\ & + b_6 \times Ethnicity + b_7 \times Garden + b_8 \times Bedroom + b_9 \times Illness + b_{10} \times Unsafe\ area \\ & + b_{11} \times Unusual\ Day \end{aligned}$$

Imputation process

Missing data on the outcome variable, 'Sleep range', and for all the covariates, were imputed using multiple imputation by chained equations (MICE), on the assumption that they were missing at random (Raghunathan, Lepkowski, Hoewyk, & Solenberger, 2001). We generated 50 imputed datasets and used Rubin's combination rules to consolidate the obtained individual estimates into a single set of multiply imputed estimates (Rubin, 1987). For the two models including the interaction term, we imputed it following standard practice (von Hippel, 2009). Calculations were performed using R (R.Core.Team, 2021) version 4.1.1 (10 August 202110) with the '*mice*' package (van Buuren & Groothuis-Oudshoorn, 2011). For reproducibility, the random seed was set equal to 123, and imputation was performed on our dataframe via the command: *mice(df, m = 50, seed = 123)* to obtain the survey design with an imputation list ('*df_survey*') prior to fitting the regression models. Our findings were reproduced and checked for convergence with a different seed and increasing imputation numbers (25, 50, 75, 100).

Weekdays versus weekends

The analysis was carried out separately for weekdays (Monday to Friday) and weekends (Saturday and Sunday), as adolescents behave differently on weekdays, when they typically must go to school, versus weekends, when they catch-up on other activities and tend to sleep later and longer (Hasler et al., 2012).

Results

Sample bias

Compared to the rest of MCS, our sample was over-indexed in middle and high-income adolescent urbanites of white origin who at the beginning of MCS, at age 9 months, were living in England in relatively advantaged areas. Their neighbourhoods at the age 14 sweep were less green, more polluted, and safer than those of their MCS peers. Table 1 includes the relevant details in terms of sample bias.

Missing values, and weekdays versus weekends

Our analytic sample of 1370 urban adolescents was made up of MCS cohort members who had lived in the same decile of neighbourhood greenspace all their lives, and who completed a TUD at age 14 (without facing technical issues for more than half of their activity tracked over two separate days). 'Objective' neighbourhood variables (e.g. for greenspace and pollution) were complete, without any missing values. All of the adolescents submitted TUD entries during a weekday (Monday to Friday), with only 28 values (2%) missing for the 'Sleep range' variable. There were 57 values (4%) missing for the 'Access to domestic garden' variable, as well as 103 values (8%) missing for 'Area safety', 'Shared bedroom', and 'Illness'. From our analytic sample, 17 cohort members did not complete the TUD during their assigned weekday but did do so during the weekend (Saturday or Sunday). This did not change the proportion of missing values, and the sample bias was essentially the same as in Table 1 above for the weekend [for instance, 685 (49%) cohort members were living in grey urban areas; 740 (53%) were female; the average level of NO_2 was 6.92].

Correlations between the main variables

To begin with we look at the pairwise correlations between greenspace, income, and sleep range (Table 2). For both weekdays (Mondays to Fridays) and weekends (Saturdays and Sundays), sleep range was not associated with either greenspace deciles or income quintiles. Greenspace and income were weakly correlated [$r(1368) = .12,\ p = .008$].

Table 1. Sample bias: variable distribution differences between the analytic sample and the rest of the MCS sample at age 14 years sweep (weighted means and %, unweighted *n*).

		Analytic sample $n = 1370$ (12%)	Rest of MCS6 $n = 10352$ (88%)	*Statistic*	*p*
Categorical variables, *n* (%)					
GSA Grey areas		673 (48%)	3984 (39%)	38.52	0.008
Other areas		697 (52%)	6360 (61%)		
Urban		1370 (100%)	7618 (77%)	335.96	<0.001
Female		741 (53%)	5097 (47%)	14.94	<0.001
Domestic garden (Yes)		1222 (89%)	8319 (75%)	84.37	<0.001
Long-term illness (Yes)		200 (16%)	1559 (16%)	0.44	0.60
Shared bedroom (Yes)		207 (15%)	1902 (19%)	22.13	<0.001
Stratum	England—Adv.	456 (55%)	2781 (43%)	3.16	0.002
	England—Disadv.	295 (25%)	2582 (33%)		
	England—Ethnic	139 (6%)	1422 (7%)		
	Wales—Adv.	66 (2%)	476 (2%)		
	Wales—Disadv.	162 (2%)	966 (2%)		
	Scotland—Adv.	93 (4%)	595 (5%)		
	Scotland—Disadv.	50 (2%)	524 (4%)		
	N. Ireland—Adv.	51 (2%)	406 (2%)		
	N. Ireland—Disadv.	58 (1%)	600 (2%)		
Ethnicity	White	1134 (84%)	7832 (76%)	21.47	0.04
	Mixed	50 (4%)	487 (5%)		
	Indian	45 (3%)	258 (2%)		
	Pakistani and Bangladeshi	76 (4%)	750 (6%)		
	Black or Black British	28 (3%)	335 (4%)		
	Other ethnic group	32 (2%)	245 (2%)		
Continuous variables, mean (*se*)					
Income (min 1, max 5)		3.62 (0.06)	2.94 (0.04)	392.22	<0.001
NO_2 (min 1, max 10)		7.39 (0.19)	6.66 (0.13)	136.92	<0.001
Unsafe area (min 1, max 4)		1.63 (0.03)	1.65 (0.01)	−37.47	<0.001

Note. Statistic and *p*-values reported are for χ^2-tests (*t*-tests) for categorical (continuous) variables. | 'Adv.' ('Disadv.') stands for Advantaged (Disadvantaged); (min *i*, max *j*) denotes the range between the minimum (*i*) and maximum (*j*) values of a continuous variable.

Table 2. Correlations between sleep range, greenspace, and income.

	Variable 1	Variable 2	*r*	*p*	*df error*
Weekdays	Income	Greenspace	0.12119	0.008	1368
	Sleep range	Income	−0.00031	> 0.999	1340
	Sleep range	Greenspace	−0.02569	> 0.999	1340
Weekends	Income	Greenspace	0.12484	0.009	1271
	Sleep range	Greenspace	0.03129	> 0.999	1240
	Sleep range	Income	−0.00592	> 0.999	1240

The unadjusted association between GSA (in deciles, in order to provide as much detail as possible) and sleep duration (in hours) is shown in Figure 1 below (based on weekday data) in the form of a bar chart.

Regression models

Full results for these models are presented separately for weekdays in Table 3 and for weekends in Table 4, and we summarise the main findings below.

Weekday analysis

There was no main effect of greenspace on sleep in either the core or adjusted versions of model 1. Except for air pollution, none of the covariates in the fully adjusted models had a significant impact on sleep range. In all models, higher levels of air pollution ('NO_2') were found to predict more sleep; for instance, in the fully adjusted model (2) we found, $b_3 = 0.068,\ t(1345) =$

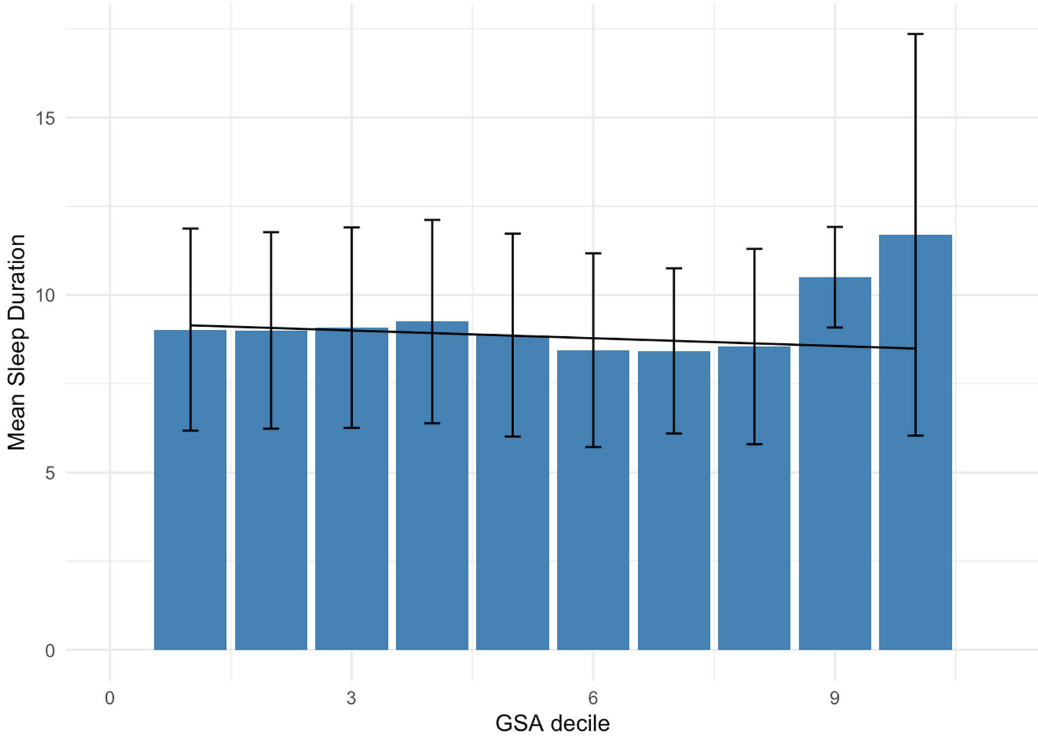

Figure 1. Mean duration of sleep (in hours) against GSA in deciles (weighted).

2.875, $p = .004$, 95% $CI[0.022, 0.114]$. We address this result separately in the discussion, after examining the weekend results as well, so that we can compare the two cases. Crucially, in the fully adjusted model, both the greenspace availability, 'GSA', $b_1 = -1.158$, $t(1345) = -3.281$, $p = .001$, 95% $CI[-1.850, -0.466]$, and the GSA-income interaction term, $b_{12} = 0.287$, $t(1345) = 3.479$, $p < .001$, 95% $CI[0.125, 0.449]$, were found to be significant predictors of sleep range, and the same held true for the corresponding minimally adjusted model (core model 2), as shown in Table 3. (We note that, in a separate sensitivity analysis, we also adjusted for the month of completion of the TUD; the effects reported here remain robust to that adjustment as well).

Figure 2 includes the interaction plot in the case of weekdays, reflecting the fact that low-income urban adolescents in greenspace-deprived areas sleep more (by around 1 h per day) than their counterparts in greener residential areas, while the gap disappears for higher-income urban adolescents.

Weekend analysis

During the weekend, urban adolescents oversleep across the board. As per the weekday analysis, there was no direct effect of greenspace or income on sleep range in model 1, with or without adjustments. This was also true for model 2 in the weekend case. Interestingly, the main effect of NO_2 on sleep range disappears on the weekend. None of the covariates in adjusted models 1 and 2 had a significant impact on sleep range, except for whether it was an 'unusual day' for the cohort member. The interaction effect of greenspace and income was still significant even in the fully adjusted model, where $b_{12} = 0.208$, $t(1362) = 2.191$, $p = .028$, 95% CI $[0.022, 0.394]$. Full details are provided in Table 4. Figure 3 includes the interaction plot, which shows the same trend as in the weekday case, namely, that low-income adolescents living in grey urban areas

Table 3. Regression coefficients for the weekday analysis (imputed, weighted data).

Coefficient (standard error)	Core model 1	Adjusted model 1	Core model 2	Adjusted model 2
Intercept	−0.620	−0.557	−0.060	0.016
	(0.317)	(0.382)	(0.332)	(0.408)
GSA: other areas	−0.064	−0.076	−1.126**	−1.158**
	(0.115)	(0.115)	(0.352)	(0.353)
INC	0.045	0.052	−0.097	−0.097
	(0.054)	(0.056)	(0.057)	(0.060)
NO_2	0.071***	0.071**	0.067**	0.068**
	(0.022)	(0.023)	(0.022)	(0.024)
Strata: E—Disadvantaged	−0.232	−0.212	−0.227	−0.205
	(0.140)	(0.143)	(0.139)	(0.143)
E—Ethnic	−0.232	−0.267	−0.463*	−0.430
	(0.188)	(0.237)	(0.193)	(0.229)
W—Advantaged	0.023	0.008	0.019	0.006
	(0.292)	(0.287)	(0.322)	(0.318)
W—Disadvantaged	0.124	0.111	0.194	0.177
	(0.188)	(0.189)	(0.206)	(0.207)
S—Advantaged	−0.026	−0.040	−0.034	−0.048
	(0.284)	(0.282)	(0.284)	(0.283)
S—Disadvantaged	−0.310	−0.292	−0.332	−0.318
	(0.331)	(0.332)	(0.327)	(0.328)
NI—Advantaged	−0.474	−0.505	−0.511*	−0.538*
	(0.273)	(0.271)	(0.259)	(0.257)
NI—Disadvantaged	0.243	0.204	0.261	0.215
	(0.267)	(0.270)	(0.290)	(0.295)
Sex: Female		0.083		0.070
		(0.098)		(0.096)
Ethnicity: Mixed		−0.267		−0.326
		(0.234)		(0.244)
Indian		−0.241		−0.172
		(0.350)		(0.321)
Pakistani and Bangladeshi		0.155		−0.038
		(0.329)		(0.291)
Black or Black British		0.030		−0.070
		(0.301)		(0.297)
Other Ethnic group		0.361		0.293
		(0.352)		(0.323)
Access to domestic garden		0.037		0.062
		(0.171)		(0.162)
Shared bedroom		0.059		0.097
		(0.158)		(0.154)
Long-term illness: Yes		−0.147		−0.156
		(0.127)		(0.123)
Unsafe area		−0.081		−0.082
		(0.107)		(0.107)
Unusual day		−0.023		−0.028
		(0.077)		(0.078)
GSA * INC interaction term			0.284***	0.287***
			(0.081)	(0.083)
R2	0.013	0.020	0.014	0.020
Nobs	1370	1370	1370	1370

Note. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$ | 'E': England; 'W': Wales; 'S': Scotland; 'NI': Northern Ireland

sleep more than their counterparts in greener neighbourhoods, even though in this case over-sleeping is the norm.

Discussion

This study explored the association between quantity of neighbourhood greenspace and adolescent sleep duration using data from MCS. Specifically, it explored whether growing up in a

Table 4. Regression coefficients for the weekend analysis (imputed, weighted data).

Coefficient (standard error)	Core model 1	Adjusted model 1	Core model 2	Adjusted model 2
Intercept	0.022	0.172	0.433	0.557
	(0.342)	(0.471)	(0.405)	(0.537)
GSA: other areas	0.150	0.131	−0.651	−0.657
	(0.114)	(0.112)	(0.404)	(0.395)
INC	0.051	0.042	−0.055	−0.065
	(0.055)	(0.057)	(0.071)	(0.073)
NO_2	0.039	0.040	0.036	0.038
	(0.025)	(0.026)	(0.025)	(0.026)
Strata: E—Disadvantaged	0.020	0.017	0.020	0.017
	(0.137)	(0.137)	(0.137)	(0.136)
E—Ethnic	−0.008	0.011	−0.179	−0.105
	(0.199)	(0.235)	(0.223)	(0.248)
W—Advantaged	0.226	0.238	0.231	0.245
	(0.219)	(0.202)	(0.224)	(0.211)
W—Disadvantaged	0.273	0.244	0.337	0.300
	(0.239)	(0.231)	(0.260)	(0.253)
S—Advantaged	−0.073	−0.072	−0.077	−0.072
	(0.166)	(0.153)	(0.177)	(0.165)
S—Disadvantaged	0.166	0.147	0.151	0.128
	(0.344)	(0.347)	(0.334)	(0.336)
NI—Advantaged	0.344	0.277	0.317	0.257
	(0.326)	(0.319)	(0.317)	(0.309)
NI—Disadvantaged	0.279	0.292	0.283	0.286
	(0.473)	(0.479)	(0.495)	(0.499)
Sex: Female		−0.020		−0.025
		(0.106)		(0.106)
Ethnicity: Mixed		−0.186		−0.227
		(0.283)		(0.286)
Indian		−0.148		−0.094
		(0.282)		(0.295)
Pakistani and Bangladeshi		0.082		−0.075
		(0.289)		(0.268)
Black or Black British		0.081		0.000
		(0.380)		(0.379)
Other Ethnic group		−0.286		−0.333
		(0.410)		(0.406)
Access to domestic garden		−0.213		−0.188
		(0.243)		(0.246)
Shared bedroom		−0.183		−0.151
		(0.173)		(0.174)
Long-term illness: Yes		−0.017		−0.031
		(0.171)		(0.168)
Unsafe area		0.001		0.010
		(0.111)		(0.109)
Unusual day		0.295**		0.292**
		(0.097)		(0.097)
GSA * INC interaction term			0.214*	0.208*
			(0.095)	(0.095)
R^2	0.003	0.013	0.007	0.016
Nobs	1387	1387	1387	1387

Note. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$ | 'E': England; 'W': Wales; 'S': Scotland; 'NI': Northern Ireland | (17 additional observations in the weekend case due to some cohort members completing the TUD then but not during their assigned weekday).

neighbourhood with low levels of greenspace was associated with deviations from the recommended sleep range among 14-year-olds living in urban areas in the UK, and whether this association varied by family income. In line with previous research into the effect of greenspace on various health outcomes in both adults and adolescents, we did not observe a direct effect of the physical characteristics of the built environment (as we measured it) on adolescent sleep, except for the case of air pollution (levels of NO_2) during weekdays only. However, when the interaction between greenspace and income was factored in, the influence of greenspace

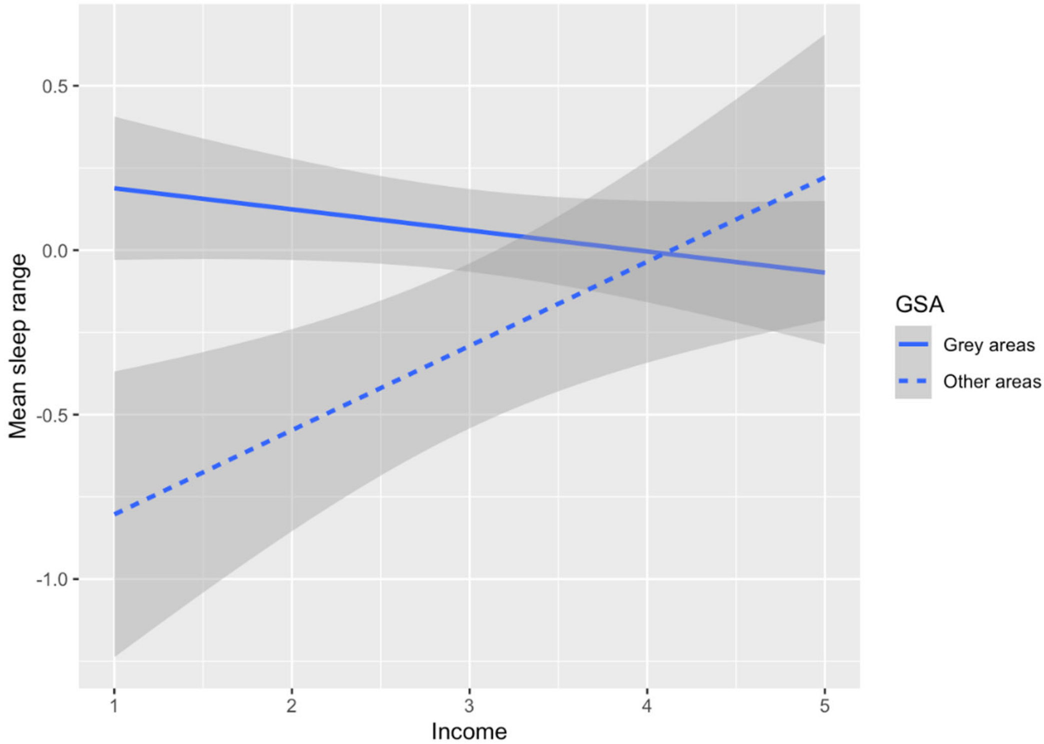

Figure 2. Interaction term plot for weekdays, showing sleep range against income in quintiles (imputed, weighted data).

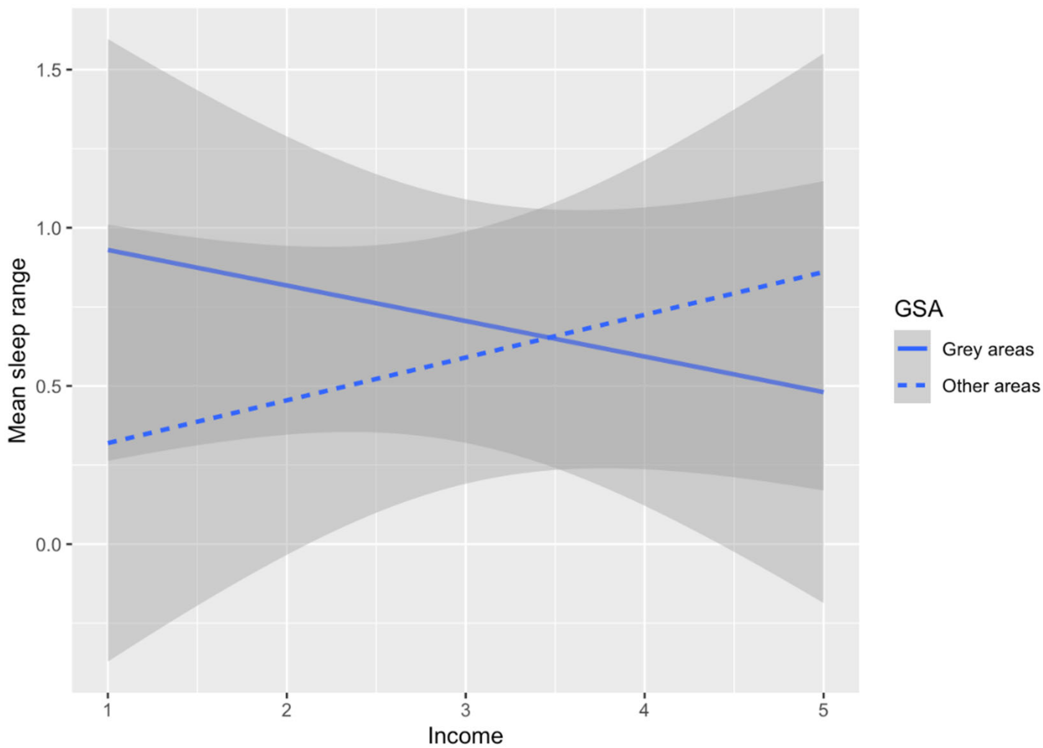

Figure 3. Interaction term plot for weekends, showing sleep range against income in quintiles (imputed, weighted data).

became evident, and we found that low-income adolescents living in grey urban areas oversleep compared to their counterparts living in greener areas, who under-sleep. In fact, in absolute terms, low-income adolescents living in greener urban areas under-sleep by a greater amount than that their counterparts in less green urban areas oversleep by. The gap in the sleep duration of adolescents with different greenspace exposures across their lifecourse narrows as their family income increases. The relationship was shown to hold for both weekdays and weekends, even though in the latter case adolescents of all backgrounds oversleep compared to the recommended range, arguably because there are no constraints around school attendance and related travel requirements. This interpretation is supported by the fact that higher levels of NO_2 predict more sleep during weekdays only, suggesting that air pollution is a proxy for road traffic (noise) and the density of an urban area. Arguably, in denser urban areas, adolescents need to travel less to get to their usual destinations (such as school or places for socialising or extracurricular activities). In turn, less travel time allows more time for sleep, as implied by a compositional analysis of the TUD activities in the MCS survey (Atkin et al., 2021).

In summary, in our urban sample, greenspace seems to differentiate sleep outcomes only among adolescents from poorer families. On school days, poorer teenagers in 'grey' areas tended to oversleep, while those in greener areas tended to sleep less than the recommended amount. The same trend was seen for weekends too, that is, poorer teenagers in grey areas were sleeping more than those in greener areas, whereas those from higher socio-economic backgrounds did not exhibit this tendency. As discussed above these findings may simply reflect the effects of transport poverty experienced by poorer families living in less dense urban areas. We can also interpret these findings however by considering the opportunities for physical activity, stress reduction, restoration and socialisation (James et al., 2015) afforded by exposure to greenspace: teenagers from low-income families in greener urban areas have relatively more access to these opportunities, and may choose to spend less time sleeping or resting in order to take part in them. By contrast, those living in the greyest urban areas do not have such an outlet. In the case of more socio-economically advantaged families, the impact of local greenspace deprivation (and associated opportunities) may be moderated by additional resources and daily structures, for instance, suitable routines and schedules, which are known predictors of adolescent well-being (Barton et al., 2019).

Our study has several limitations. First, it is correlational, so we cannot determine whether, for example, the association between living in grey areas and oversleeping among low-income urban adolescents is causal and not due to residual confounding. Second, our measure of greenspace availability up to age 14 years (in 2015) made use of data from 2001. Due to the limitations of the MCS data we had available, our analysis could not factor in any changes in the built environment and greenspace availability over time. Nevertheless, based on the evidence available, it can be argued that UK neighbourhoods' contextual characteristics (such as public greenspace) do not change substantially over a decade in recent history (Gambaro, Joshi, & Lupton, 2017). Importantly, there was also no information available about the quality of greenspace and the various types of greenness, which arguably may be more relevant than our measure, i.e. the proportion of greenspace in the neighbourhood. On the other hand, we did account for the interrelated environmental factor of air pollution (NO_2 levels), which can also be used as a proxy for urban neighbourhood density and traffic noise in our sample. Third, we had no data on the cohort members' proximity to and use of greenspace, nor did we know if there was accessible greenery available to them in adjacent neighbourhoods, for instance, in the case of urban adolescents living near ward boundaries. Fourth, time-use diary entries were available on only two occasions for every cohort member, and we have no objective sleep measures with which to compare the accuracy of the self-reported sleep durations.

However, the present study also has significant strengths, including the use of data from a large and nationally representative birth cohort, and the use of time-use diaries in middle adolescence. The dataset also allowed us to consider a variety of potential confounders, on three levels starting from the wider ecology of the urban environment (air pollution and, by proxy, traffic noise), to various area and family-level covariates (such as area socio-economic disadvantage, perceived neighbourhood safety, family income, and access to a domestic garden), to individual-level factors that included sex, ethnicity, sharing of a bedroom, and chronic health conditions. Future work should address the aforementioned limitations, and also consider the misalignment between weekday and weekend sleep.

In conclusion, supporting previous findings (Mueller & Flouri, 2021), the present study suggests that merely increasing the amount of greenspace in residential neighbourhoods may not be sufficient to promote better outcomes for urban teenagers. Any policy implications of our work in relation to sleep health in adolescence should consider the complex interaction between neighbourhood greenspace and family income.

Disclosure statement

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Data availability statement

The data that support the findings of this study are available from the Millenium Cohort Study, UK Data Service of the University of Essex, University of Manchester and Jisc (https://ukdataservice.ac.uk/). The dataset is available from the UK Data Service by application, under licence.

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