Artificial Light at Night and Obesity: Does the Spread of Wireless Information and Communication Technology Play a Role?

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Abstract

Purpose: Artificial light at night (ALAN) may influence body mass via different mechanisms, including the suppression of the melatonin production by direct ALAN exposure, and by causing a shift in the food intake, due to activities enabled by ALAN. In the present paper, we attempt to separate these potential mechanisms by introducing measures of Internet and cellular phones use that reflect the proliferation of information and communication technologies (ICT) in individual countries of the world.
Methods: In addition to ICT measures, our multivariate regression models link country-specific obesity rates with ambient ALAN levels, captured by satellite sensors, with per capita GDP, urbanization, birth rate, food consumption and regional differences.
Results: As the analysis reveals, in low-income countries, the number of cellular phone subscriptions emerged as a statistically significant predictor of obesity rates ($t>2.386$; $P<0.05$), while in the rest of the world countries, obesity was found positively related to ALAN ($t>2.251$; $P<0.05$), but not to Internet and cellular phone use ($P>0.1$).
Conclusion: We explain these differences by the fact that Internet and cellular phones are widely spread in low resource countries, and their use may become an effective circadian disruptor, despite relatively low ambient ALAN levels, attributed to limited economic resources available.

Keywords: Artificial light at night (ALAN), Internet usage, Cellular subscriptions, Obesity prevalence rate

1. Introduction

As recent empirical studies show, ALAN may influence body mass via different impact mechanisms, including the suppression of melatonin production, changing the metabolic function [1, 2] and shifting the time of food intake by moving it from active to the rest phase [3, 4]. However, to the best of our knowledge, none of these studies attempted to separate these potential impact mechanisms, an issue we attempt to address in this paper.

In a recent study [5], the authors tested the extent to which artificial light-at-night (ALAN) helps to explain the obesity prevalence rates observed in more than 80 countries worldwide and obtained from the World Health Organization. As the study revealed, population-weighed ALAN levels, obtained from the U.S. Defense Meteorological Satellite Program, were positively associated with female ($t=2.739$, $P<0.01$) and male ($t=2.658$, $P<0.01$) obesity rates, reported for individual countries of the world [6].

However, satellite images, used in [5], do not represent the whole picture. The matter is that, due to a rapid proliferation of cellular telephones and Internet technology, people worldwide are currently exposed to ALAN, not captured by any satellite. Although ipads, cellular phones, PC, gaming devices do not emit much light, they are

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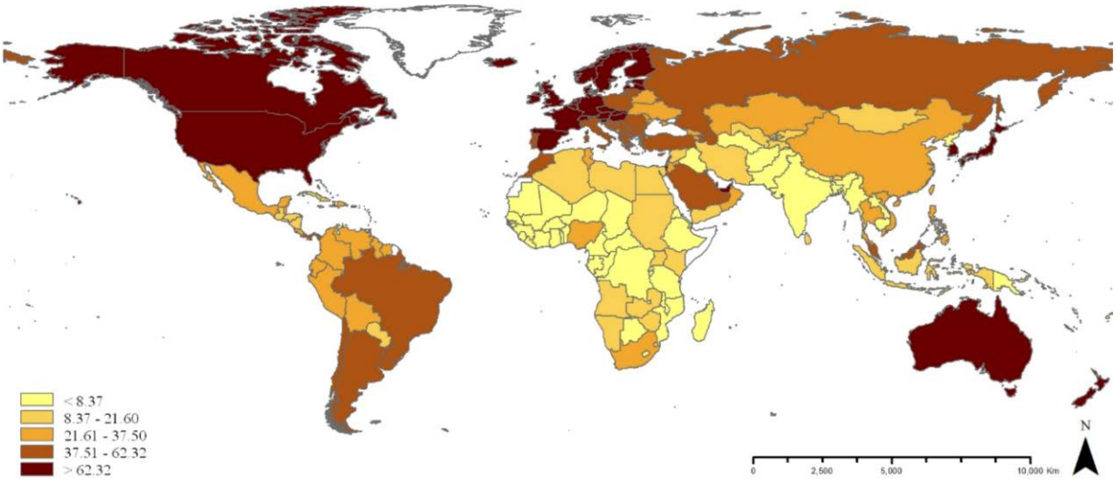
very effective in melatonin suppression, not only because they are kept close to the eyes, but also due to the “blue” short wavelength light they emit [7]. In addition, cellular phones and Internet, which are widely spread even in least developed countries and often used after the natural dusk and at night, may serve as distinctive measures of circadian disruption on their own right, especially in places, where people have no opportunities for nighttime outdoor activities enabled by ALAN in more developed countries.

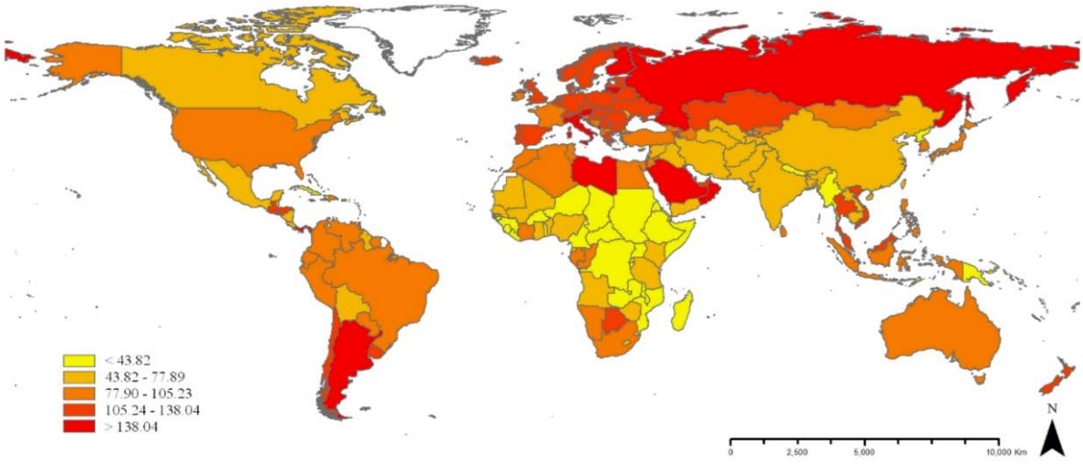
2. Methods

In this reanalysis of the ALAN-obesity rate association, we retain the general research setting and modelling approach used in [5], but add the computers and cellular phones usage to the list of explanatory variables for country-specific obesity rates, considering that the use of such devices can be a proxy for indoor ALAN exposure not captured by satellite sensors.

Relevant data on the percent of Internet users and the number of cellular subscriptions per 100 persons were obtained from the International Telecommunication Union [8] and shown in Fig. 1.



(A)



(B)

Fig. 1. Worldwide rates of: (A) Internet usage (% of total population) and (B) cellular phone subscriptions (number per 100 persons)

3. Results

The results of analysis are reported in Table 1, both for females and males (Table 1)[1]. As Table 1 shows, the number of cellular subscriptions emerged as statistically significant positive predictor for female obesity prevalence rates (t=2.005; P<0.05; see Model 2; Table 1). However, this variable did not emerge as a significant predictor in the male obesity model (t=1.172; P>0.1; see Model 4; Table 1).

Table 1. Factors affecting female & male obesity prevalence rates in individual countries of the world (dependent variables – female & male obesity prevalence rates, % of adult population; method – OLS regression)

Predictors	Model 1		Model 2		Model 3		Model 4	
	Ba	(t)b	Ba	(t)b	Ba	(t)b	Ba	(t)b
(Constant)	2.796	(4.761)***	2.154	(3.252)***	2.492	(2.692)***	1.762	(1.583)
GDP per capita (current US$)	-3.24E-05	(-4.550)***	-3.15E-05	(-4.478)***	-8.49E-06	(-0.920)	-8.62E-06	(-0.937)
Urban population (% of total)	0.022	(3.214)***	0.019	(2.687)***	0.019	(1.811)*	0.017	(1.699)*
Birth rate (per 1000 persons)	-0.037	(-3.087)***	-0.026	(-1.965)*	-0.047	(-2.089)**	-0.035	(-1.431)
ALAN (dimensionless units)	0.002	(2.739)***	0.002	(2.426)**	0.003	(2.658)***	0.003	(2.331)**
Oils, fats, sugars (calories per day)	0.001	(2.393)**	0.001	(2.480)**	0.001	(2.077)**	0.001	(2.226)**
Roots, tubers (calories per day)	-0.002	(-3.739)***	-0.002	(-3.681)***	-0.003	(-2.772)***	-0.003	(-2.781)***
SIDS in the Pacific	2.990	(5.939)***	3.094	(6.189)***	3.148	(4.928)***	3.241	(5.048)***
Asia	-2.530	(-7.419)***	-2.409	(-7.043)***	-3.025	(-6.289)***	-2.883	(-5.825)***
Cellular phone subscriptions per 100 persons	–	–	0.006	(2.005)**	–	–	0.005	(1.172)
N of obs.	129		129		84		84	
R2	0.727		0.736		0.679		0.685	
R2-adjusted	0.709		0.716		0.644		0.646	
F	(39.948)***		(36.850)***		(19.802)***		(17.842)***	
SEEc	0.923		0.912		1.097		1.094	

Notes: BMI≥30 cut-off point for obesity rate (WHO, 2014). *Indicates a 0.1 two-tailed significance level; **Indicates a 0.05 significance level; ***Indicates a 0.01 significance level. a Unstandardized regression coefficient; b t-statistic; c Standard error of the estimate.
Model 1: Basic female model reported in Rybnikova et al (2016).
Model 2: Female model with the number of cellular phone subscriptions added as an additional predictor.
Model 3: Basic male model reported in Rybnikova et al (2016).
Model 4: Male model with the number of cellular phone subscriptions added as an additional predictor.

We decided to look into the differences between male and female models further and reran the analysis separately for countries with different income levels. Our motivation was as follows: by contrast to female obesity rates, which are available for a relatively large pool of 129 countries, data on male obesity rates are currently available only for countries with relatively high income levels (84 countries).

For the country breakdown we used the World Bank income classification, which denotes countries with annual GDP per capita of less than US $1000 as low-income (LI) countries [9]. Concurrently, countries with more than $1000 per capita per annum we refer to as above-low-income (ALI) countries. The analysis is performed for female obesity rates only, because, as we previously mentioned, data on obesity rates in males are unavailable for LI countries. The results of re-analysis are reported in Table 2.

[1] Due to a multicollinearity consideration, we introduced the internet users and cellular subscriptions variables into the models se parately. In the following discussion, only the best performing models are reported.

Table 2: Factors affecting female obesity prevalence rates in LI and ALI countries (dependent variable – female obesity rate, % of adult female population; method – OLS regression)

Predictors	Model 5		Model 6	
	Ba	(t)b	Ba	(t)b
(Constant)	2.943	(4.039)***	-0.134	(-0.087)
GDP per capita (current US$)	-2.59E-05	(-3.534)***	0.000	(-0.346)
Urban population (% of total)	0.013	(1.657)	0.021	(1.025)
Birth rate (per 1000 persons)	-0.013	(-0.876)	0.004	(0.143)
ALAN (dimensionless units)	0.002	(2.251)**	0.006	(0.796)
Oils, fats, sugars (calories per day)	0.001	(2.235)**	0.001	(0.437)
Roots, tubers (calories per day)	-0.002	(-3.150)***	-0.001	(-1.676)
SIDS in the Pacific	2.663	(5.210)***	–	–
Asia	-2.728	(-7.175)***	-1.409	(-1.924)*
Cellular Subscriptions, per 100 persons	0.002	(0.481)	0.026	(2.386)**
N of obs.	103		26	
R2	0.617		0.628	
R2-adjusted	0.580		0.453	
F	(16.635)***		(3.593)**	
SEEc	0.902		0.682	

Notes: BMI≥30 cut-off point for obesity rate (WHO, 2014). *Indicates a 0.1 two-tailed significance level; **Indicates a 0.05 significance level; ***Indicates a 0.01 significance level. a Unstandardized regression coefficient; b t-statistic; c Standard error of the estimate.
Model 5: ALI countries.
Model 6: LI countries.

As Table 2 shows, ALAN emerged as a significant variable in the model estimated for female obesity rates in ALI countries (t=2.251; P<0.05; see Model 5; Table 2), while the cellular phone subscription variable is insignificant in this model (t=0.481; P>0.1; Model 5; Table 2). By contrast, the model estimated for LI countries, reports no significant association between female obesity rates and ALAN (t=0.796; P>0.1; Model 6; Table 2), while there is a significant and positive association between cellular phone subscriptions and female obesity rates (t=2.386; P<0.05 in Model 6; Table 2).

4. Discussion and Conclusion

The present analysis is a continuation of the previous study [5], which reported a positive association between outdoor ALAN and adult overweight and obesity prevalence rates in world countries. In this study, we retain the modelling approach used in [5], while adding the Internet usage and cellular subscriptions to the list of explanatory variables in multivariate regression models for country-specific obesity rates, considering these variables as proxies for indoor ALAN exposure. We estimated ALAN-obesity associations separately for men and women, living in low-income (LI) and above-low-income (ALI) countries.

As the analysis reveals, in low-income countries, the number of cellular phone subscriptions is as a statistically significant predictor of obesity rates (t>2.386; P<0.05), while in the rest of the world countries, obesity was found positively related to nighttime outdoor light (t>2.251; P<0.05), but not to Internet and cellular phone use (P>0.1). We explain these differences by the fact that Internet and cellular phones are widely spread in low resource countries, and their use may become an effective circadian disruptor, despite relatively low ambient ALAN levels, attributed to limited economic resources available.

The use of cellular phones and Internet has become increasingly common, even in less developed countries. However, these devices are an unqualified ALAN source by satellite sensors, and any analysis which does not take the use of these devices into account, may lead to biased results. The matter is that these devices emit short wavelength light, nighttime exposure to which is known to lead to an effective suppression of the rhythmicity of melatonin production and may become an effective circadian disruptor on its own, potentially influencing body mass by shifting the time of food intake. Moreover, low quality cellular phones and tablets are often sold in underdeveloped countries, where mass consumers cannot afford more expensive devices. The screens of such low quality devices are likely to have less protection against shortwave (blue) light, compared to higher quality devices sold in more developed countries. The use of such low quality devices may result in a stronger effect on melatonin suppression and circadian disruption.

A stronger effect of cellular phone use on women than on men, which our study also revealed (see Models 2 and 4 in Table 1), may be due to more extensive cellular phone use by females or, alternatively, to higher susceptibility of females to harmful effects associated with frequent cellular phone use. However, this hypothesis needs to be confirmed by further analysis, which should be performed separately for low-income and above-low-income countries, and, separately, for men and women. However, possibilities for such an analysis are currently limited due to limited data availability.

Several limitations of the study should be mentioned. First and foremost, the present study is a geographical analysis and its results cannot be considered as a proof of causality. In addition, as we previously mentioned, data on obesity prevalence rates are available for women and not available for men in low income countries. For that reason, our findings need to be confirmed by further studies, as data on obesity prevalence and indoor ALAN proxies become available for more countries and regions.

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