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Original Article

The Effect of Human Development Index on Obesity Prevalence at the Global Level: A Spatial Analysis

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Abstract

Background: Obesity is one of the major public health concerns, and its prevalence is increasing worldwide. This study aimed to investigate the effect of human development index on the prevalence of obesity across 152 countries.

Methods: Country-level data on obesity prevalence and its influencing variables related to 152 countries were obtained during 2000-2019 from several sources. A Spatial Bayesian Hierarchical model was employed in this research, and the analyses were performed using R statistical software (version 3.6.1).

Results: We found a positive relation between HDI and obesity prevalence, in such a way if low HDI countries advance to high HDI countries, the obesity rate is expected to increase significantly by 7.45%. Moreover, the association between obesity prevalence and the percentage of people aged 40-59 (β=0.07), urbanization rate (β=0.11), percentage of internet users (β=0.01), percentage of alcohol users (β=0.16), milk consumption per capita (β=0.15) and Percentage of depression (β=0.58) was significantly positive. Conversely, per capita consumption of fruits and vegetables (β=-0.15), and smoking rate (β=-0.02) was negatively associated with obesity prevalence.

Conclusion: The prevalence of obesity is growing across all countries, especially in the countries with high and very high HDI. Therefore, policymakers must also pay attention to the negative effects of development when trying to improve the welfare of society.

Keywords: Obesity; Human development index; Sociodemographic factors; Lifestyle factors

Introduction

Obesity is one of the greatest public health problems of the modern world that has reached pandemic status in the last 50 years (1). In 2016, 650 million people up to 13% of the adult population suffered from obesity (BMI≥30 kg/m2) across the globe (2), and the number of obese people is expected to reach 1.2 billion by 2030 (3).

Obesity affects almost all physiological functions of the body, and it is one of the leading risk factors for cardiovascular diseases, diabetes type2, and various cancers (4). Such that 4.7 million deaths globally are attributable to overweight and obesity (5).

Obesity is higher in very high human development (HDI) countries compared to low human development countries which this issue is related to lifestyle changes and other obesity determinants. Changes in lifestyle and dietary behaviors is patterned by the level of development and obesogenic environmental factors such as socioeconomic status (SES). However, the impact of socioeconomic status as an indicator of lifestyle on the prevalence of obesity is intricate and not completely understood (6). The association of obesity prevalence and SES varies depending on the country's level of HDI. In such a way, obesity affects lower SES groups more in higher HDI countries (7). However, the association between SES and obesity prevalence was positive in countries with low level of HDI. Various studies have investigated socio-economic factors affecting obesity including age, gender, marital status, educational attainment, residential area, occupational status, and financial condition, which showed conflicting results of the association between SES and obesity (8, 9).

Besides social and environmental conditions, behaviors such as poor nutrition, physical inactivity, sedentary lifestyle (10), and depression (11) were also identified as the most important obesogenic behaviors. One of the main ingredients of lifestyle is the diet that can play a crucial role in the development of obesity (12). Dietary patterns containing less fruit and vegetables (13), dairy products (14, 15), and high-meat diets (16) have been linked with higher obesity prevalence. Although the effects of dairy products and meat consumption on body weight have been unequivocal in numerous studies, some studies have concluded that protein-enriched diets and lower dairy intake were beneficial in losing weight (17-19).

Furthermore, sedentary time, smoke, and alcohol consumption are other unhealthy lifestyle habits in the occurrence of obesity (20). The effects of smoking and alcohol drinking on obesity have been also broadly examined in various studies that have presented contradicting results. Some research suggested an inverse association (9, 13, 21, 22) and others a positive association (21, 23-25).

Therefore, due to the contradictions of research findings in different countries and since studies on obesity and its influencing factors have been conducted using individual or household data, it is necessary to conduct a study at the global level to obtain a comprehensive insight on determinants of obesity. To the best of our knowledge, this analysis is the first to investigate the effect of HDI and other sociodemographic and behavioral lifestyle factors on obesity in 152 countries. Identifying the determinants of obesity guides policymakers in the adoption of strategies for the prevention and control of obesity epidemic.

Methods

We constructed a data set covering 152 countries from 2000-2019 to evaluate the association of HDI, sociodemographic and behavioral lifestyle factors with obesity prevalence. We divided countries into four tiers according to the HDI as having a low (27 countries), medium (28 countries), high (41 countries), or very high HDI (56 countries) because HDI is a comprehensive indicator for assessing the level of welfare and development of countries and it is a composite scale to rank countries based on 3 criteria: life expectancy, education, and gross national income (GNI) per capita (PPP$). The HDI value is between 0 and 1. The HDI figure shows how much each country has tried to achieve the highest possible value (i.e., one) (26). HDI is the most influential variable and other variables are sub-variables that affect each country belongs to which HDI and obesity groups. Our goal was to evaluate the effects of different levels of HDI on obesity and a series of other covariates that could affect this relationship were also included in the model.

Definition of covariates

Obesity prevalence was the response variable and the explanatory variables included sociodemographic factors (gender, percentage of the population aged 40-59, urbanization rate, and unemployment rate) and behavioral determinants (fruit and vegetable consumption, meat consumption, milk consumption, percentage of internet users (as a proxy of sedentary behaviors) (27), smoking rate, alcohol intake, and depression rate). Table 1 list all variables with their definitions and sources.

Table 1: Variables, their definition and sources

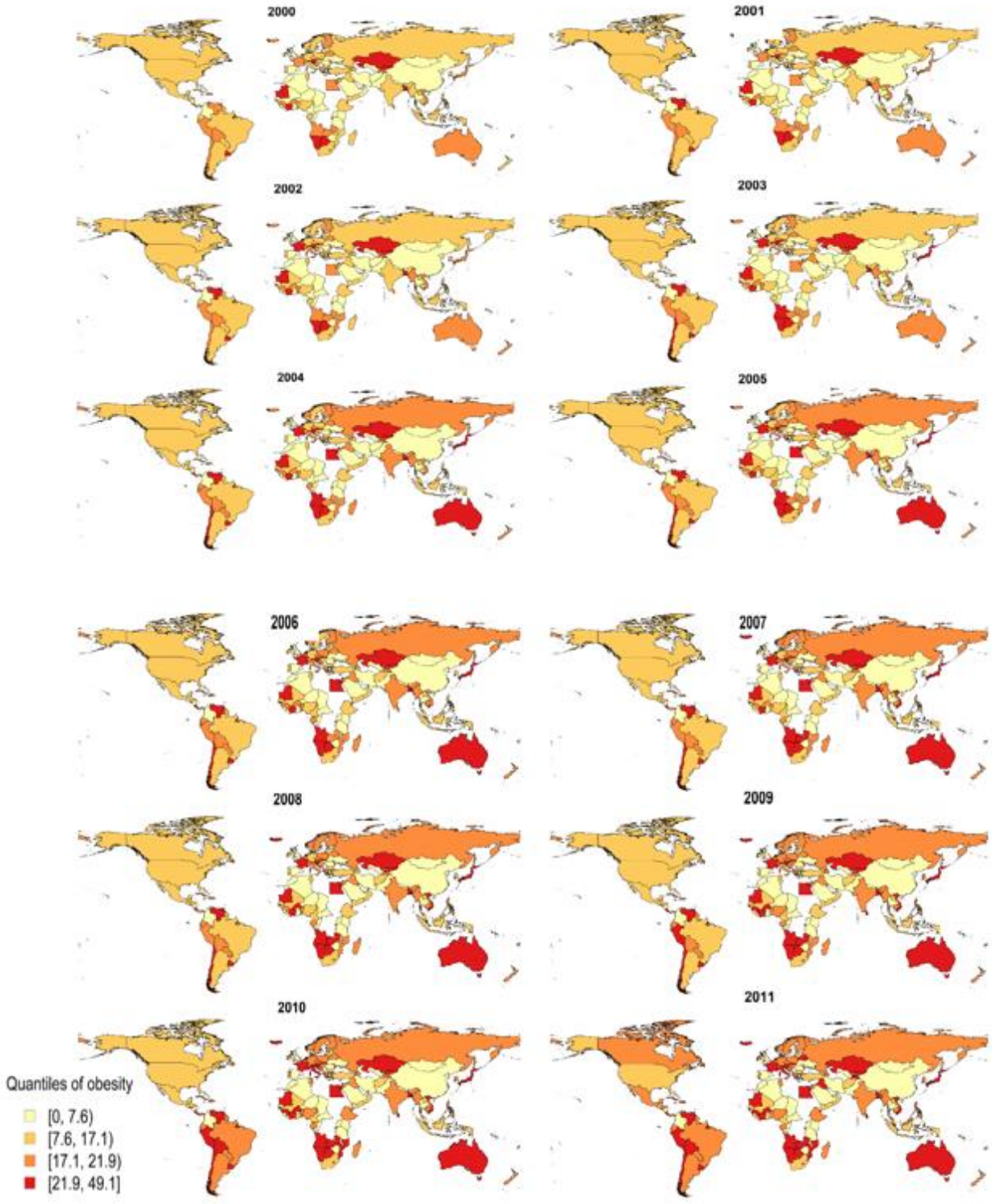
Variables	*Definition*	*Sources*
Obesity prevalence	Obesity is defined as BMI≥ 30 kg/m2	WHO (2)
Middle-aged adults	The group of people aged 40–59 was used to describe the middle-aged adults	UN (28)
Urbanization rate	The percentage of people who are inhabitants of urban areas according to definition by the national statistical offices	UN (28)
Unemployment rate	The percentage of labor force who does not have a job but is available for work and actively looking for it.	WBG (29)
Per capita fruit and vegetable consumption	It measured in kilograms per person per year.	OWID (30)
Per capita meat consumption	It measured in kg per person per year and does not include seafood and fish.	OWID (30)
Average per capita milk consumption	It measured in kg per person per year and includes any of the products derived from milk except Butter.	OWID (30)
Percentage of internet users	Share of people who have used the internet in the past 3 month.	WBG (29)
Smoking rate	The proportion of individuals aged 10 and over who smoke daily.	GBD (31)
Percentage of alcohol users	The prevalence of alcohol consumption that was measured by the summary exposure value for alcohol use.	GBD (31)
Depression rate	Share of the population suffering from depressive disorders.	OWID (30)

Ethical Approval

This research is part of a Ph.D. dissertation which approved in the Ethics Committee of Tehran University of Medical Sciences: No.IR.TUMS.SPH.REC.1397.288.

Statistical modeling

A Bayesian hierarchical modeling framework with a Gaussian response distribution for data analysis employed. 152 countries were considered as the areal units. Countries which close to each other tend to have the same characteristics as countries that are far apart, and this is the most significant property of spatial data analysis. Spatial models emerge when data is collected over time and space and have at least one spatial and temporal property. Also, looking at the amounts of observed obesity for each of the 152 countries (Fig. 1), it is clear how obesity prevalence is increased in 20 years almost for all countries, which could be explained by including a temporally random effect in the model.


2000
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Quantiles of obesity
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[17.1, 21.9)
[21.9, 49.1]

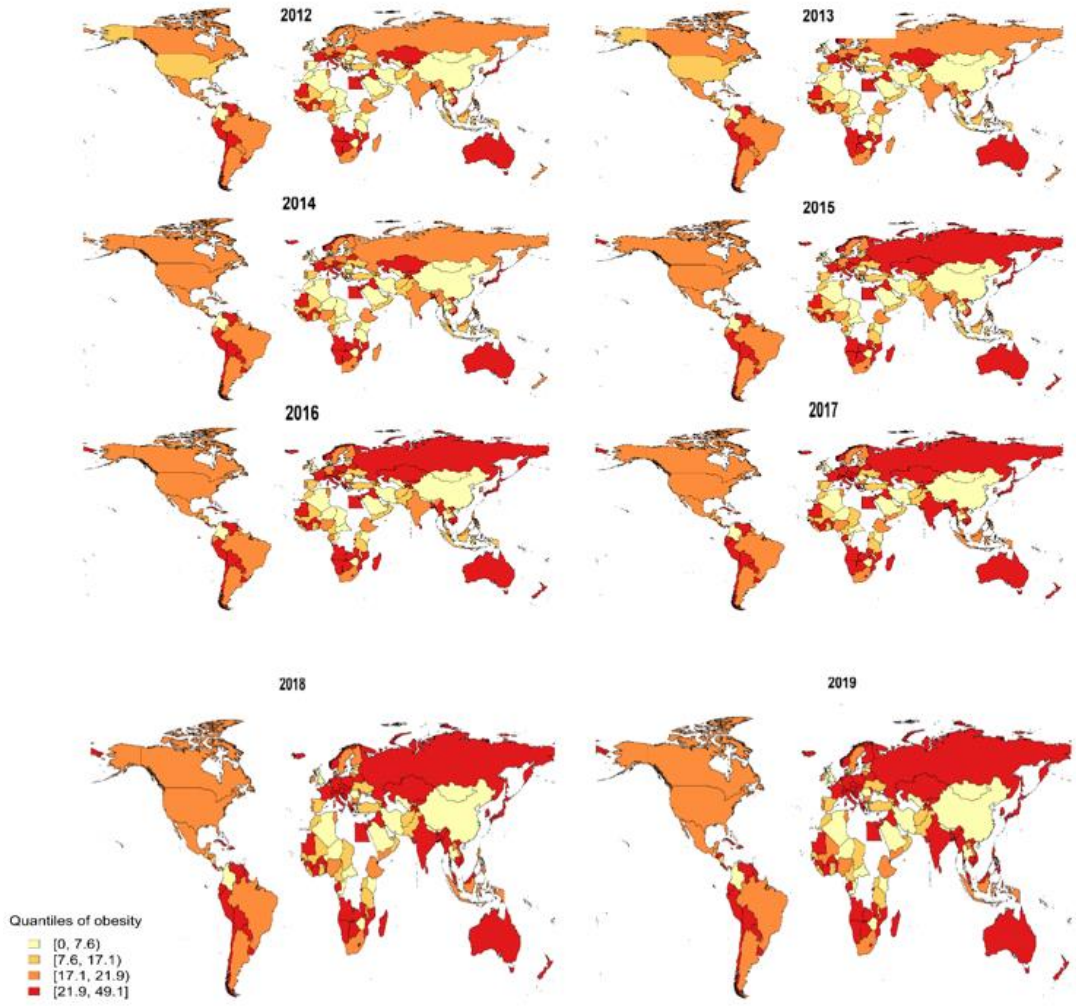

Fig. 1: Spatial distribution of the prevalence of obesity in 152 countries from 2000-2019.

Therefore, we have a Spatio-temporal model which the data are defined with space (i) and time (t) indexed. Allowing interaction between space and time (δ_{it}), the model is formulated using the following specification:

$$Y_{it} \sim N(\mu_{it}.\sigma^2). \quad i = 1.\ldots.152. \quad t = 1.\ldots.20$$

$$\mu_{it} = X_{it}^T\beta + (\theta_i + \varphi_i) + (\gamma_t + \upsilon_t) + \delta_{it}$$

Let y_{it} denote the prevalence of obesity in country i at year t which follows a Gaussian distribution. In this model, X is the matrix of covariates, $(\theta_i + \varphi_i)$ are structured and unstructured spatial random effects and $(\gamma_t + \upsilon_t)$ are structured and unstructured temporal random effects. We fitted four models with different types of interactions between spatial and temporal random effects and compared with Deviance Information Criterion (DIC) and Watanabe-Akaike Information Criterion (WAIC). The best model with lower values of both DIC and FfiWAIC assumes that the temporal dependency structure for each country depends on the temporal pattern of the neighboring countries as well. We evaluated the impact of HDI categories on the prevalence of obesity after adjusting some covariates. Diffuse priors were used for the model parameters. Parameter estimation was implemented using Integrated Nested Laplace Approximation (INLA) in the INLA package in R statistical software (version 3.6.1).

Results

As presented in Table 2, the highest and lowest rate of obesity was observed in very high HDI countries and countries with low HDI respectively. The mean percentage of middle-aged people was higher in countries with very high HDI, as such, the highest percentage of men was attributable to countries with very high HDI and these countries had also the highest degree of urbanization rate. Regarding the unemployment rate, high HDI and low HDI countries had the highest and lowest rate of unemployment respectively. By upgrading a country's level of development, lifestyle factors have also changed. So that very high HDI countries recorded the highest level of smoking, alcohol intake, using internet, fruit and vegetable consumption per capita, meat intake per capita, and milk consumption per capita.

In Fig. 2, countries with very high HDI had the highest levels of obesity prevalence, followed by countries with high HDI.

Table 2: Descriptive statistics of the countries based on different levels of HDI (2000-2019)

Variable	***HDI groups***											
	Low N= 27			***Medium N= 28***			***High N= 41***			***Very high N= 56***		
Covariates	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max	Mean (SD)	Min	Max
Obesity	7.13 (3.90)	1.9	25.4	10.85 (7.24)	0.6	34.1	17.92 (8.41)	2.4	49.1	21.08 (6.11)	2.1	39.4
Urbanization	34.72 (14.22)	14.61	61.93	41.54 (16.08)	13.39	77.91	57.12 (17.76)	18.05	91.99	74.45 (14.16)	31.14	100.00
% Of Age (40-59)	12.35 (1.41)	9.73	16.73	14.99 (3.12)	10.04	28.60	21.02 (4.53)	11.29	31.94	26.04 (3.33)	13.15	34.49
% Of Male	49.71 (0.90)	47.65	51.61	49.66 (1.12)	45.43	53.38	49.89 (1.52)	46.32	63.29	49.79 (3.81)	45.78	74.80
Unemployment rate	6.22 (5.72)	0.31	16.80	6.72 (5.16)	0.39	35.26	9.98 (7.49)	0.48	37.25	7.58 (4.10)	0.80	27.46
Smoking rate	11.12 (3.88)	3.73	18.99	15.59 (7.07)	3.57	34.07	20.07 (6.74)	7.56	38.78	23.83 (7.26)	6.42	38.36
Alcohol intake	7.8 (5.5)	0.32	19.54	8.91 (5.29)	0.04	36.54	12.17 (6.80)	0.00	33.74	19.68 (7.85)	0.31	36.09
Internet users	7.06 (9.62)	0.00	33.00	13 (14.16)	0.00	76.12	27.77 (21.94)	0.09	84.21	57.84 (26.72)	2.21	100.00
Depression	3.78 (0.57)	2.53	5.47	3.46 (0.65)	2.23	5.75	3.14 (0.58)	2.19	5.17	3.55 (0.66)	2.24	5.34
Fruit and vegetable intake	86.64 (61.64)	12.73	369.76	121.53 (69.30)	20.76	406.57	198.49 (96.87)	28.57	549.10	204.56 (68.65)	82.90	487.33
Meat intake	14.55 (7.18)	2.79	37.90	21.53 (11.25)	3.40	100.68	45.57 (22.37)	3.93	111.31	74.57 (20.31)	34.07	126.17
Milk consumption	29.08 (28.41)	1.17	111.12	53.50 (51.75)	0.78	226.75	90.38 (62.16)	1.55	404.21	192.32 (84.60)	16.44	463.91

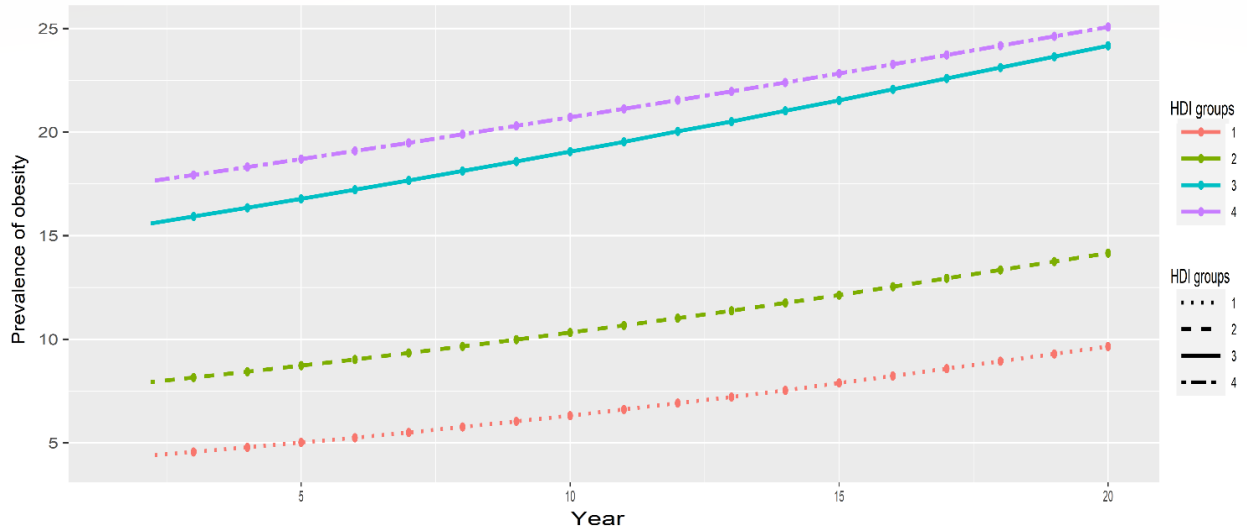

Fig. 2: Trend of obesity by different levels of HDI for 2000-2019
**1= Low HDI, 2= Medium HDI, 3= High HDI, 4=Very high HDI*

Based on the results of Table 3, if low HDI countries transition to high HDI countries, the obesity rate is expected to increase by 7.45%. By keeping the other variables constant, per unit increase in the percentage of people aged 40-59 years increased significantly the rates of obesity by 0.07%. Similarly, for a percentage increase in the urbanization rate, a 0.11% increase in the prevalence of obesity was observed.

Table 3: The effects of HDI, sociodemographic and behavioral lifestyle factors on obesity prevalence

Variables	***Mean (SD)***	***2.5% quant***	***97.5% quant***
Intercept	-0.024 (0.570)	-1.143	1.094
Low HDI	baseline		-
Medium HDI	-0.188 (3.021)	-6.171	5.733
High HDI	7.458 (2.811)*	1.827	12.908
Very high HDI	1.316 (3.074)	-4.754	7.366
Percentage of age(40-59)	0.074 (0.014) *	0.047	0.102
Urbanization rate	0.112 (0.010)*	0.093	0.132
Percentage of male	0.034 (0.020)	-0.004	0.073
Unemployment rate	0.000 (0.004)	-0.008	0.008
Percentage of internet users	0.012 (0.001)*	0.010	0.015
percentage of alcohol users	0.162 (0.012)*	0.139	0.186
Log(Average consumption of fruits and vegetables)	-0.148 (0.054)*	-0.254	-0.042
Log(Average milk consumption)	0.155 (0.028) *	0.099	0.210
Log(Average meat consumption)	-0.086 (0.064)	-0.212	0.041
Smoking rate	-0.027 (0.011) *	-0.048	-0.005
Percentage of depression	0.582 (0.208) *	0.176	0.991

Notes:*Significant at 0.05. SD: Standard deviation

The percentage of male population (0.03) had a positive and not significant correlation with obesity prevalence. Regarding the impacts of internet use on obesity, per unit increase in the percentage of internet users was significantly associated with a 0.01% increase in obesity prevalence. Likewise, for a 1% increase in alcohol intake, there was a 0.16% increase in obesity prevalence. On the contrary, obesity prevalence decreased by 0.14% as the average consumption of fruits and vegetables increased by 1 unit. Moreover, per unit increase in milk consumption per capita was on average linked to a 0.15% rise in obesity prevalence. The effect of meat consumption on obesity was negative but not significant (-0.086). Smoking showed an inverse and statistically significant correlation with obesity, so a 0.02% fall in body weight was associated with a 1 unit rise in smoking rate. Further, the results illustrated that the prevalence of obesity increased by 0.58% per one unit increase in depression rate.

Discussion

In this study, we found that obesity prevalence is increasing in all the studied countries particularly in countries with very high and high HDI. Based on the results, the obesity rate increased as countries with a low level of HDI moved to countries with high HDI, these findings were supported by other studies (26, 32). Income, welfare status of people, and nutritional habits such as eating processed and high-calorie foods, technological innovations, and subsequently sedentary lifestyle increase which all have a role in the spread of obesity (33). Out of sociodemographic determinants, there was a significant and positive correlation between people aged 40-59 years and obesity. This finding was consistent with some past studies (34,35). Several studies have documented that obesity increases with age and reaches its peak in middle age and declines in older ages. With aging, due to low physical activity, sedentary lifestyle, and hormonal changes, the risk of obesity increases (34), but during old age, people lose their appetite, they are less likely to eat and feel less hungry, and lose weight frequently due to weakness, morbidity, and imminent death (36).

As previously reported (9, 10, 37) a significant positive relationship was also found between urbanization and obesity rates, and this could be related to the fact that urban dwellers have different lifestyles compared to villagers. There is less opportunity for physical activity and most people engage in sedentary jobs that contribute to obesity (37). However, some studies have reported that obesity prevalence is rising in rural areas more than in cities (23, 38).

Regarding behavioral factors, a significant positive association was seen between using the internet and obesity prevalence, this finding was supported by some previous studies (15, 20, 27). Despite our results, one study reported a negative association (39). One of the direct effects of using the internet on obesity was physical inactivity, by sitting in front of a computer for long hours a day. Excessive use of the internet increased energy intake by high snack consumption, causes sleep deprivation and thus indirectly leads to obesity (27).

Likewise, we found that the consumption of fruit and vegetable reduces the prevalence of obesity significantly which agreed with other studies (13, 20, 21). The abundance of water and fiber content in fruits and vegetables contributes to satiation, suppresses the feeling of hunger, and attenuates energy intake (40). However, some studies suggested that consumption of fruits and starchy vegetables have been positively associated with body weight (41,42).

Given our findings, milk consumption had a significant positive impact on obesity prevalence. Similarly, Berkey et al. and Lahti-Koski et al. confirmed our findings (17, 18). Other studies have suggested an inverse relation (14, 15). One possible reason that can explain the positive effect of milk consumption on obesity may be the stimulation of IGF-1. Milk proteins have been shown to enhance the secretion of a growth hormone called insulin which causes cell proliferation in connective and musculoskeletal tissue (43).

We found a negative effect of smoking on obesity, and the finding was supported by some past stud-

ies (9, 21). In contrast, some published studies reported a positive association (23, 25). The negative effect of smoking on obesity could be related to the fact that smoking suppresses appetite and body weight by raising the metabolic rate and energy expenditure and a decrease in metabolic efficiency or calorie intake (44).

In terms of alcohol consumption, several studies supported our findings that alcohol use had a positive and significant association with obesity prevalence (21, 24) due to low nutritional value and main source of calories (24). On the contrary, some studies found a negative association (13, 22). Further, a significant and positive correlation of depression with obesity echoed the results of some past studies (11, 45). Common risk factors in depressed people that lead to obesity include adopting a sedentary lifestyle, a decline in physical activity, emotional eating and reducing sleep time (11, 46). This study had some limitations. First, data quality varied from country to country. Some countries had good data reporting systems, while others relied on data estimates to fill their data gaps. Second, in the present study, no data is available at the individual level. So, the results should not be extrapolated to individual-level communications.

Conclusion

Obesity is one of the major public health problems that has affected all countries of the world, especially countries with very high levels of development. Such an increase in the prevalence of obesity could be related to factors such as access to technology, the development of countries, and consequently lifestyle changes. Therefore, policymakers must pay attention to the side effects of improving the welfare and development of countries, such as increasing the prevalence of obesity, and take preventive measures to control this epidemic.

Journalism Ethics considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

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Conflict of Interest

The authors declare that there is no conflict of interests.

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