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Original Article

Multilevel Analysis of Socio-Demographic Disparities in Adulthood Obesity Across the United States Geographic Regions

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ABSTRACT

Objectives: The objective of this study was to examine the socio-demographic disparities in obesity among US adults across 130 metropolitan and micropolitan statistical areas.

Methods: This study used data from the 2015 Behavioral Risk Factor Surveillance System and Selected Metropolitan/Micropolitan Area Risk Trend of 159,827 US adults aged 18 years and older. Data were analyzed using the multilevel linear regression models.

Results: According to individual level analyses, socio-demographic disparities in obesity exist in the United States. Individuals with low socioeconomic status were associated with a higher body mass index. The participants from the Midwest United States tend to have higher body mass index than those who from the South. According to metropolitan and micropolitan statistical area level analyses, secondly, there were significant differences in obesity status between different areas and the relation of obesity with 5 socio-demographic factors varied across different areas. According to geospatial mapping analyses, even though obesity status by metropolitan and micropolitan statistical area level has improved overtime, differences in body mass index between United States regions are increasing from 2007 to 2015.

Conclusion: Socio-demographic and regional disparities in obesity status persist among US adults. Hence, these findings underscore the need to take socio-environmental factors into account when planning obesity prevention on vulnerable populations and areas.

Introduction

Obesity has become a nationwide epidemic in the United States. The prevalence of obesity among adults (> 20 years) has consistently increased from 2001 to 2014 [1]. Obesity is linked to increased risk for non-communicable diseases including cancer, difficulty with physical movement, heart disease, mental illness, osteoarthritis, sleep apnea, stroke, and Type 2 diabetes [2-5]. Obesity and overweight together are the second leading cause of preventable death (approximately 300,000 deaths per year) in the United States, right after cigarette smoking [6,7].

Previous studies have reported that obesity rates vary greatly between socio-demographic groups in the United States. Specifically, a larger ratio of individuals are overweight or obese among lower income groups, lower-educated groups, Non-White or Hispanics than among other socio-demographic groups [8-10]. Women have lower obesity rates than men for self-reported height and weight [8,11-13]. However, other studies have shown that even though the mean body mass index (BMI) is lower for women than men, women are gaining weight quicker than men [14]. There may no longer be a difference between men and women based on measured height and weight [9]. According to the National Health and

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Nutrition Examination Survey 2015-2016, the prevalence of obesity was 35.7% among young adults aged 20-39 years, 42.8% among adults aged 40-59 years, and 41.0% among adults older than 60 years of age showing that middle age and older groups had higher obesity rates than young adult groups in the United States [15]. It has been reported that there are geographical disparities in obesity in the United States [16-20]. According to national statistics, the Southern states have higher prevalence of obesity compared to other states [21,22].

The social cognitive model of reciprocal determinism proposes that environmental factors influence individuals, groups, and their behaviors [23]. In other words, regional differences in health behavior caused by various environmental factors could lead to different health outcomes according to geographical areas. Specifically, social epidemiological research has reported that the geographical context in which people live is related to health disparities [24-28]. In terms of obesity, regional difference in lifestyle factors, environmental factors, health care resources, and socioeconomic status have been found to affect disparities in risk factors for obesity in the United States [29-34].

Previous studies have focused on county levels to determine adulthood obesity, but little is known about geographical disparities in adulthood obesity by metropolitan and micropolitan statistical area (MMSAs) levels in the United States. Thus, the objective of this study was to examine the socio-demographic disparities in adulthood obesity and examine how this relationship is affected by geographic areas (130 MMSAs). The following associated hypotheses were examined in this study:

(1) Socio-demographic disparities in adulthood obesity persist among US adults

(2) Participants from the South MMSAs areas have higher BMI compared to those who reside in other MMSAs areas.

(3) Obesity and socio-demographic status are influenced by geographic areas (130 MMSAs).

Materials and Methods

This study used data from the 2015 Behavioral Risk Factor Surveillance System (BRFSS) and Selected Metropolitan/Micropolitan Area Risk Trends (SMART). The BRFSS is the nation's premier system of health-related telephone surveys that collected state data on US residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services. Established in 1984 in 15 states, BRFSS now collects data in 50 states as well as the District of Columbia and 3 United States territories. BRFSS completes more than 400,000 adult interviews each year, making it the largest continuously conducted health survey system in the world. BRFSS data are generally used to provide state-level estimates. BRFSS and SMART data are used to provide small area-level estimates for MMSAs which were determined by the Office of Management and Budgets. Hence, in order to create localized health information that can help public health practitioners identify local emerging health problems, plan and assess local responses, the Centers for Disease Control and Prevention analyzes BRFSS and SMART data. This specific data selected for this study was from 2015 and was city and countywide including 159,827 US adults aged 18 years and older [35]. This study did not require approval from the institutional review board because the BRFSS data was secondary data that did not include personal information.

1. Why MMSAs selected rather than another type of local administrative unit?

MMSAs represent geographic areas that satisfy standard definitions determined by the United States Office of Management and Budget (OMB), which are used by the Census Bureau and other federal, state, and local governmental entities. MMSAs consist of counties and the BRFSS collects data about county of residence. This county information allows the reporting of information by MMSAs. Some cities and counties were excluded from SMART and BRFSS. In order for an MMSA to be included in SMART BRFSS there must be at least 500 respondents within the MMSA and the weighting criteria must be applicable. In order for a county to be included, the county must be within a selected MMSA and the weighting criteria must be applicable at the county level. The State's BRFSS Coordinator handles these cases [35].

2. Measures

2.1. Dependent variable: obesity

BMI was used as a measure of obesity and it was computed by dividing an individual's weight by their height squared. BMI is closely linked with percentage body fat and total body fat [36]. Individuals with a BMI of 25 kg/m^2 to 29 kg/m^2 were regarded as overweight, and individuals with a BMI of 30 kg/m^2 or more were considered obese [37].

2.2. Independent variables: socio-demographic variables

Gender was categorized into males and females. Age was categorized into 18-44 years and ≥ 45 years. The education level was categorized into higher education (≥ college diploma) and lower education (< college diploma). Race was categorized into Non-White or Hispanic and Non-Hispanic White. The household income level was categorized into ≥ \$50,000 and < \$50,000. Regions were categorized into 5 groups (South, Northeast, Midwest, West, Puerto Rico).

2.3. Control variables

Physical activity was categorized into yes and no. Fruit consumption was categorized into ≤ 1 time per month and ≥ 1 time per week.

3. Statistical Analysis

Descriptive statistics with using chi-square (Table 1) and line graph analysis are presented in Figure 1. All descriptive analyses were carried out using STATA (version 15.0, StataCorp LLC., College Station, TX).

A mainland United States map of average adult BMI (≥ 18 years) by MMSAs levels in 2007, 2011, and 2015 was created using Arc GIS 10.6 with R (Figure 2).

To examine the socio-demographic and regional disparities

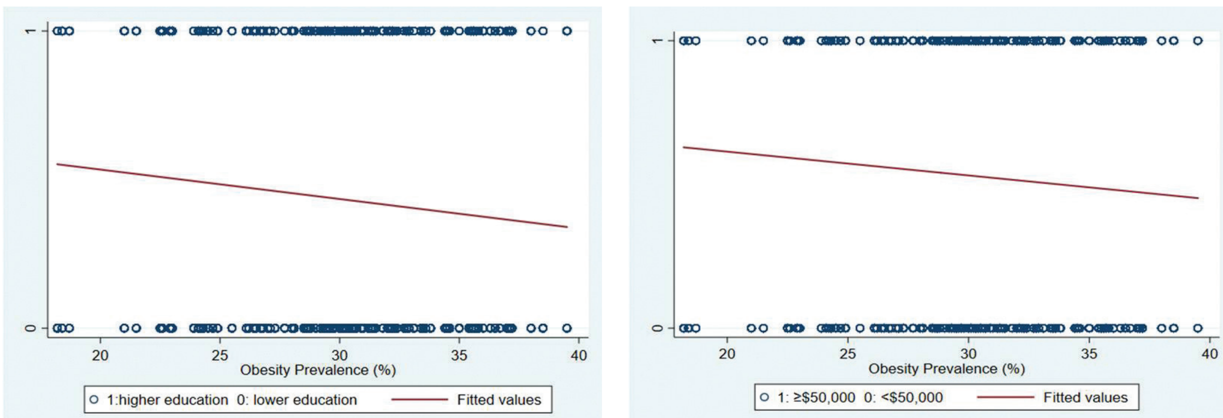

Figure 1. The association between the prevalence of obesity according to area (130 MMSAs) and socioeconomic status (education level and income level).
MMSA = metropolitan and micropolitan statistical area.

Table 1. Demographics and population characteristics (*N* = 159,827), BRFSS and SMART, 2015.

		n (%)	Obesity rate (%)
Individual level			
Gender	Male	71,987 (45.04)	29.41
	Female	87,840 (54.96)	29.15
Age (y)	≥ 45	114,822 (71.84)	30.60
	18-44	45,005 (28.16)	25.87
Education level	≥ College	71,091 (44.48)	24.05
	< College	88,736 (55.52)	33.45
Race	Non-White or Hispanic	37,020 (23.16)	33.38
	Non-Hispanic White	122,807 (76.84)	28.03
Income level	≥ $50,000	86,331 (54.02)	26.05
	< $50,000	73,496 (45.98)	33.05
Region	South	44,932 (28.11)	31.08
	Northeast	32,401 (20.27)	29.96
	Midwest	46,575 (29.14)	31.65
	West	33,372 (20.88)	25.72
	Puerto Rico	2,547 (1.59)	29.88
MMSA level (*n* =130)			
% of obese people in the MMSA where participants live (mean, SD)		29.06	4.44

BRFSS = behavioral risk factor surveillance system; MMSA = metropolitan and micropolitan statistical area; SMART = selected metropolitan/ micropolitan area risk trends.

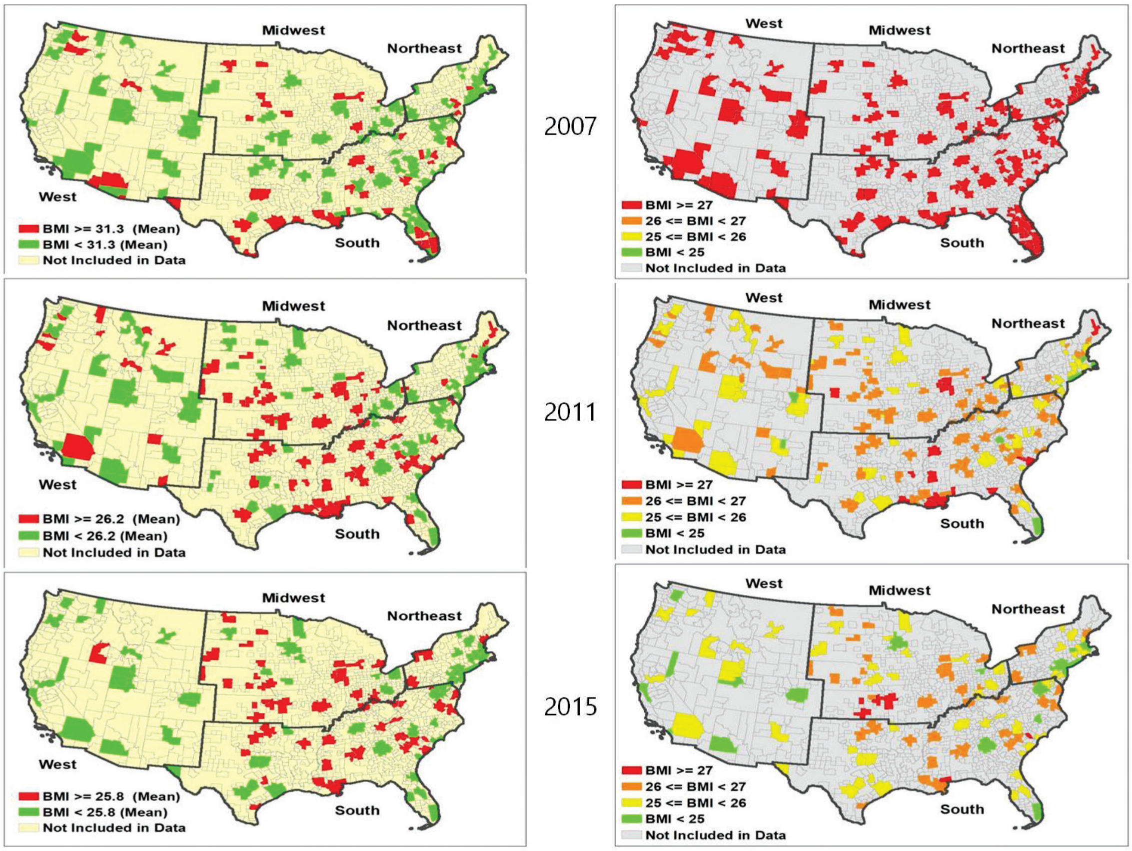

Figure 2. Mainland United States map of average adult BMI (≥ 18 years) by MMSAs levels in 2007, 2011, and 2015: BRFSS, CDC.
BMI = body mass index; BRFSS = behavioral risk factor surveillance system; MMSA = metropolitan and micropolitan statistical area.

in adulthood obesity among US adults across 130 MMSAs, 3 multilevel linear regression models of BMI were conducted using STATA. Firstly, the null hypothesis model was implemented (Model Ⅰ) to determine whether there was a difference in obesity status and these statistical areas. Secondly, the random-intercepts model (Model Ⅱ) was implemented which considers individual-level predictors in the fixed part to examine how the 6 socio-demographic variables affect obesity status after adjusting for obesity-related health behaviors such as physical activity and fruit consumption. Finally, the random-slope model (Model Ⅲ) was implemented to examine whether or not obesity status and with the 5 socio-demographic variables varied across the 130 MMSAs.

Results

Table 1 shows the percentages of obesity rate among US adults ≥ 18 years (*N* = 159,827). The average percentage of obese people (BMI ≥ 30) in the 130 MMSAs was 29.06% (SD = 4.44). Men were slightly more likely to be obese than women (29.41% versus 29.15%). Participants who were ≥ 45 years were more likely to be obese than those aged 18-44 years (30.60% versus 25.87%). Participants with a higher education (≥ college diploma) were less likely to be obese than those who had a lower education (< college diploma) (24.05% versus 33.45%). Non-White or Hispanic participants were more likely to be obese than Non-Hispanic White participants (33.38% versus 28.03%). Participants with a higher income (≥ $50,000) were less likely to be obese than those with lower income (< $50,000) (26.05% versus 33.05%). Participants from the South and the Midwest were more likely to be obese than those from the Northeast and the West (31.08% and 31.65% versus 29.96% and 25.72%).

Table 2 shows the results of multilevel linear regression of socio-demographic status and BMI among US adults (≥ 18 years) in 130 MMSAs (*N* = 159,827). The average coefficient of Model Ⅰ was 28.147. The metropolitan and micropolitan

Table 2. Multilevel linear regression of socio-demographic status and BMI among US adults (≥ 18 years) (N = 159,827).

		Model Ⅰ		Model Ⅱ		Model Ⅲ	
		Coef	(SE)	Coef	(SE)	Coef	(SE)
Fixed effect (individual level)							
Intercept		28.147***	(0.071)	27.105***	(0.103)	27.058***	(0.118)
Gender	Male			0.600***	(0.033)	0.592***	(0.040)
	Female (Ref)						
Age (y)	≥ 45			0.721***	(0.037)	0.709***	(0.052)
	18-44 (Ref)						
Education level	≥ College			-0.790***	(0.036)	-0.743***	(0.049)
	< College (Ref)						
Race	Non-White or Hispanic			1.067***	(0.043)	1.008***	(0.079)
	Non-Hispanic White (Ref)						
Income level	≥ $50,000			-0.295***	(0.037)	-0.292***	(0.039)
	< $50,000 (Ref)						
Region	Northeast			-0.359*	(0.166)	-0.293	(0.195)
	Midwest			0.432**	(0.142)	0.504**	(0.165)
	West			-0.657***	(0.160)	-0.576**	(0.187)
	Puerto Rico			-1.468*	(0.618)	-1.227	(0.927)
	South (Ref)						
Physical activity	No			1.800***	(0.040)	1.800***	(0.040)
	Yes (Ref)						
Fruit consumption	≤ 1 per mo			0.427***	(0.036)	0.422***	(0.036)
	≥ 1 per wk (Ref)						
Random effect (Between MMSAs)							
Intercept		0.774***	(0.053)	0.596***	(0.043)	0.653***	(0.053)
Slopes for gender						0.192***	(0.052)
Slopes for age						0.350***	(0.046)
Slopes for education level						0.324***	(0.052)
Slopes for race						0.654***	(0.073)
Slopes for income level						0.106***	(0.078)

*p < 0.05, **p < 0.01 ***p < 0.001
BMI = body mass index; MMSA = metropolitan and micropolitan statistical area.

statistical area level residual variance at Model Ⅰ was significant at the 0.001 level, which means that there were significant differences in obesity status between the 130 MMSAs. Model Ⅱ, Ⅲ show the unstandardized coefficients from the multilevel linear regression model of the association between socio-demographic variables and obesity status among US adults. According to full model (Model Ⅲ), firstly, men were associated with higher BMI than women (B = 0.592, p < 0.001). Secondly, participants who were ≥ 45 years were associated with higher BMI than those aged 18-44 years (B = 0.709, p < 0.001). Thirdly, participants with higher education (≥ college diploma) were associated with lower BMI than those who with lower education (< college diploma) (B = -0.743, $p < 0.001$). Fourthly, Non-White or Hispanic participants were associated with higher BMI than Non-Hispanic white (B = 1.008, $p < 0.001$). Fifthly, participants with higher income (≥ $50,000) were associated with lower BMI than those who with lower income (< $50,000) (B = -0.292, $p < 0.001$). Finally, participants from the Midwest MMSAs areas were associated with higher BMI than those who from the South MMSAs areas (B = 0.504, $p < 0.01$). On the other hand, participants from the West MMSAs areas were associated with lower BMI than those who from South MMSAs areas (B = -0.576, $p < 0.01$).

Random slope model (Model Ⅲ) analysis shows that the metropolitan and MMSA-level residuals were all significant at the 0.001 level. It means that the obesity status relationship with the 6 socio-demographic variables varies across the 130 MMSAs.

Figure 1 displays the association between prevalence of obesity according to the areas (130 MMSAs) and socioeconomic status such as education levels and household income levels. As shown in Figure 1, areas with a higher prevalence of obesity tended to have a higher proportion of people with a lower level of education and a lower household income.

Figure 2 displays a mainland United States map of the average adult BMI (≥18 years) by MMSAs levels in 2007, 2011, and 2015. As shown in maps on the left, the mean BMI of all MMSAs has decreased overtime. As shown in both maps, there were no significant differences in BMI according to regions in 2007. However, over time, differences in BMI between the regions widened.

Discussion

This study is one of the first studies in the United States to examine socio-demographic and regional disparities in adulthood obesity by MMSAs. Multilevel analysis was used to examine the socio-demographic disparities in obesity and examine how this relationship is affected by the geographic areas (130, MMSAs).

1. The association between socio-demographic factors and obesity status

This study observed that men, ≥ 45 years, with a low level of education (< college diploma), who are Non-White or Hispanic, with a low income (< $50,000) were more likely to have higher BMI than other socio-demographic groups. This finding was consistent with the hypothesis that socio-demographic disparities in obesity status persist among US adults. The findings are similar to those reported in previous studies [8-13,15]. In addition, participants from the Midwest MMSAs areas were more likely to have a higher BMI than those from the South MMSAs areas. This finding was inconsistent with the hypothesis that participants from the South MMSAs areas have higher BMI compared to those from other MMSAs areas.

This finding is different from those reported in previous studies [21,22]. Public health authorities need to increase their efforts to reduce obesity rate targeting residents in the Midwest, although it is possible that the difference between county level analysis and MMSAs level analysis caused different results.

2. How socio-demographic factors and obesity status are affected by the geographic areas.

This study observed firstly that there were statistically significant differences in obesity status between different areas (130 MMSAs). Secondly, the relationship between obesity and 5 socio-demographic factors varied across different areas (130 MMSAs). Thirdly, areas with a higher prevalence of obesity tended to have a higher proportion of individuals with a low socioeconomic status (Figure 1). Fourthly, as shown in Figure 2, even though obesity status by MMSA levels has improved overtime, BMI differences between United States regions are increasing (2007 to 2015). There were no significant regional differences in BMI in 2007, but a higher BMI was more prevalent in the Midwest and the South MMSAs areas in 2015. Specifically, the highest BMIs are concentrated in MMSAs in the Midwest such as Wichita (State of Kansas), Topeka (State of Kansas), and Kansas City (State of Missouri). This finding was consistent with the hypothesis that obesity among US adults and socio-demographic status are influenced by geographic areas (130 MMSAs). La Veist [38] in 2003 and Williams and Collins [39] in 2001 reported that individuals from vulnerable groups generally live in geographically separate communities in the United States and this residential segregation can cause different environmental and social risk exposures [38,39]. In terms of obesity, socio-environmental factors are potential influential factors for the prevalence of obesity in the United States [29-34]. Hence, individual characteristics are not likely to be the major cause of the obesity epidemic in the US, whereas socio-environmental factors play a leading role. Furthermore, individuals from low socioeconomic status communities in the United States were associated with high obesity rates caused by inactive lifestyles, easy access to energy-dense food, and limited access to healthy food [40-43]. This is supported by observations presented in table 2 (Model Ⅱ and Model Ⅲ) and Figure 1. Regionally, in 2017, the median income in the West was $67,517, the Northeast, $66,450, the Midwest, $61,136, and the South, $55,709. Therefore, the Midwest and the South have a lower median household income compared with the West and the Northeast [44]. In 2018, 39.8% of residents in the West, 42.8% in the Northeast, 35.9% in the South, and 37.9% in the Midwest had a higher degree (post-secondary degree). This indicated that the Midwest and the South had a lower levels of educational attainment than the West and the Northeast [45]. Hence, it is possible that lower socioeconomic status could increase the risk of obesity among residents in the South and the Midwest of the United States.

In this situation, developing policies that concentrate on revising social aspects of the environment such as promoting active lifestyles, controlling access to unhealthy food, and improving access to healthy food may decrease disparities in obesity among socio-demographic groups living in different areas. Lin et al in 2011 observed that a hypothetical 0.5 cent-per-ounce tax on sugar drink could reduce consumption of about 40-51 calories per day among children and 34-47 calories per day among adults [46]. Han et al in 2012 reported that subsidizing to healthy food resulted in a larger decrease in BMI among The Supplemental Nutrition Assistance Program (SNAP) participants [47]. Policies are guided by the social cognitive model of reciprocal determinism. Specifically, reciprocal determinism emphasizes the interaction between people and their environments [23,48]. It means that environmental factors influence individuals, groups, and their behavior, but individuals and groups can also influence their environments and regulate their own behavior. Therefore, this theory highlights disease prevention policies and promotion of public health by changing environmental factors that can have positive effects on human health and behavior [23,48].

Adult obesity rates have continued to increase in the United States [1]. Obesity is connected to an elevated risk of non-communicable diseases including cancer, difficulty with physical movement, heart disease, mental illness, osteoarthritis, sleep apnea, stroke, and Type 2 diabetes [2-5]. With these health complications, obese people are facing a huge economic burden related to higher medical costs [49-51]. Due to the social and health implications of obesity, it is necessary to develop tailored and effective obesity prevention programs for US adults that consider socio-environmental factors.

The observations of this study should be considered in light of several limitations. Firstly, the temporal causal relationship between 5 socio-demographic variables and the obesity status cannot be determined because the study design was cross-sectional. Therefore, follow-up studies that are a prospective longitudinal design are needed to verify the findings of this study. Secondly, this study was based on self-reported socio-demographic and obesity status. It is possible that participants could not answer their socio-demographic and obesity status precisely, which might lead to inaccurate estimations of socio-demographic and obesity status. Thirdly, this study could not address the specific causes of regional disparities in obesity in the United States. Hence, follow-up studies are needed.

Conclusion

Despite the limitations of this study, identifying the socio-demographic and regional disparities in adulthood obesity using large sample size data, provided meaningful results. This study's finding also provides socio-environmental implications to prevent and reduce obesity US adults. Methodologically, this study was significant in the sense that it was one of the first attempts to apply MMSAs level data to analyze socio-demographic and regional disparities in adulthood obesity in the United States. The MMSAs level data-method employed in this study yielded a more specific estimate of the obesity status in adults in the US metropolitan and micropolitan areas.

In conclusion, socio-demographic and regional disparities in obesity status persist among US adults. Hence, these findings underscore the need to take socio-environmental factors into account when planning obesity prevention interventions in vulnerable populations and areas. For example, policies that improve social aspects of the environment such as promoting active lifestyles and securing access to healthy food may reduce socio-demographic and regional disparities in obesity.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to this research, authorship, and/or publication of this article.

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