Obesity; Spatial Accessibility and SEIFA Case Study: Greater Melbourne Area (GMA)

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Abstract

Today, the inequality of distribution of built environments leads to the formation of advantaged and disadvantaged neighborhoods. Advantage neighborhoods have good accessibility (Distance to) and availability (Number of) service centers. If the neighborhoods have some service centers that don't provide healthy lifestyles, especially in increasing obesity, they can decline community health in these areas. So, this research tries to have a spatial view of obesity as a dependent variable. Independent variables are the number of and distance to food, smoking, and physical activity centers that are based on theoretical concepts. We analyzed them with dependent variables on SEIFA Clusters at SA2 level. This research has used spatial analysis methods such as BILISA Cluster on Local Moran I for clustering, GWR for spatial correlation which is a base of the analysis method. The results in the Great Melbourne Area (GMA) show that the level of accessibility is more important than availability and some SA2s in the low levels of SEIFA haven't good access to a healthy built environment and which makes them more obese.

Highlights

- Accessibility is more important than availability;
- Advantage neighborhoods have good accessibility (Distance to) and availability (Number of) service centers;
- There is a positive relationship between obesity and food centers and physical activity centers and a negative relationship between obesity and smoking and drinking centers

1. Introduction

According to statistics published by the World Health Organization in 2022, over 1 billion people worldwide are obese, and by 2025, approximately 167 million people will face health problems because of being overweight or obese (World Obesity Atlas, 2022) (WHO, 2022). The prevalence of obesity is not the same in all regions. Obesity is an emerging public health concern in Australia. Obesity is the second disease-causing risk factor in Australia (after tobacco use), causing 4.8% of the total disease burden (Keramat, 2021). Obesity is defined as having a body mass index (BMI) equal to or greater than 30. The latest data from the National Health Survey 2017–18 suggests that almost a third of Australian and Victorian adults are obese (Australian Bureau of Statistics 2018). Neighborhood socioeconomic status (SES) is often associated with individual health outcomes. People living in high-SES neighborhoods have better health than people living in low-SES neighborhoods (Fan, et al. 2020). The conceptual equivalent of SES in Australia is the SEIFA index; each geographical region in Australia is given a score based on its social and economic conditions, which measures the degree of "advantage" or "disadvantage" of that area compared to other regions of Australia (Hanson, et al. 2021; Kerr, et al. 2021). This index is the analytical basis of this article. Research has shown that obesity also follows this pattern, with people living in low-SES neighborhoods experiencing higher odds of obesity compared to people living in high-SES neighborhoods (Fan, et al. 2020). The social determinants of health are non-medical factors and can affect a person's health (Daniel, 2018). These practices include eating habits (fast foods), smoking, drinking alcohol, exercise, and similar behaviors that are characteristics of certain social groups and classes in different lifestyle patterns (Mollborn, 2021).

Being overweight and obese is caused by a chronic excess of caloric intake compared to energy expenditure, which is probably caused by an imbalance in caloric intake, sedentary behaviors, and physical inactivity (Ross, et al. 2016) (Romieu, et al. 2017). In the last two decades, there has been a paradigm shift in obesity research, mainly focusing on the drivers of such "obesogenic" behaviors (Lakerveld, J., & Mackenbach, J. 2017). While previous research focused on individual-level factors such as knowledge, psychological constructs such as motivation, and genetics, more recent epidemiological research places obesity in a larger social-ecological context in which the environment also plays a role in shaping individual behavior. It has (Lakerveld, J., & Mackenbach, J. 2017) (Roberto, et al. 2015). The built environment has been hypothesized as a potential spatial stimulus in the occurrence of obesity (Lam, et al. 2021). Therefore, the built environment is defined as all aspects of the environment around a person who are made or changed by humans, such as buildings, parks, facilities and infrastructure (Vineis, et al. 2017), this built environment by Activities and spaces are defined whose accessibility has a great impact on a person's physical activity as well as reducing or increasing obesity.

Melbourne is the case study of this article. The city has 309 SA2 census blocks at the medium level. Therefore, all data are pooled for different variables and modeling purposes. The unit of analysis is SA2. Acceptable sample size and ease of access to data at
this level are among the factors for choosing it as the basis for data collection. This data is from the latest Australian census in 2023, which is updated annually. This study examines the geographic characteristics of the obesity epidemic in the Greater Melbourne Area (GMA). It also examines how the spatial distribution of the built environment in SEIFA clusters affects changes in obesity, and the characteristics of the built environment, such as access to food centers, physical activity centers, and smoking & drinking centers, affect the pattern of obesity epidemic changes in the place. So, research questions can be:

- What are the spatial patterns of obesity changes in GMA?
- Obesity in which SEIFA cluster has the highest number of patients in GMA?
- What are the most effective spatial factors among access or accessibility to food centers, physical activity centers, and smoking & drinking centers, in obesity changes in GMA?
- What policy implications at the LGA (Local Government Area) decision-making level may be drawn from this research?

The structure of this article is, at first, due to the weakness of previous approaches to spatial analysis related to the growing trend of obesity, we try to examine the quality of access to food centers, physical activity centers, and smoking & drinking centers in SEIFA clusters and let’s identify its relationship with changes in obesity (availability or accessibility). A combination of statistical analysis models and spatial analysis forms the methods of this article. We used bivariate correlation, spatial clustering (Space-Bivariate Local Moran’s I), and Geographically Weighted Regression methods to evaluate the relationship between built environment variables in significant clusters of High obesity-Low SEIFA, and Low obesity-High SEIFA in SA2 scale.

2. Literature Review

Increased physical activity is associated with a reduced risk of obesity. Neighborhood characteristics (e.g., parks, green spaces, physical activity facilities) are important determinants of physical activity, especially in disadvantaged neighborhoods (Cereijo, et al. 2022; Gillies, et al. 2007; Johnson, et al. 2013; Kriska, et al. 2021). Increasing physical activity opportunities at the neighborhood level is associated with reduced obesity. For example, greater availability of green and open spaces is associated with a lower incidence of obesity. However, few studies have investigated the relationship between the availability of physical activity spaces and obesity (Cereijo, et al. 2022). Past research has shown that adequate facilities for physical activity, including parks and green spaces, can reduce health inequalities (Cereijo, et al. 2022). Studies assessing the potential influence of neighborhood physical texture have found that the availability of physical activity opportunities, such as parks or recreational facilities, is positively associated with physical activity levels (Kufman, et al. 2019). Environmental factors have important effects on changes in physical activity levels and changes in eating behaviors throughout life, these changes and the effect of these factors according to the socioeconomic level are the focus of obesity research. Considering the environmental effects on physical activity, it is possible to identify the relationship between environmental and social factors in the neighborhood environment. These factors in the environment include urban configuration, access to healthy food, access to sports centers, and the social environment of the neighborhood (Congdon, 2019).

Urban Configuration and Physical Activity Particularly in the United States, Canada, and Australia, there is extensive literature on the urban configuration in terms of its impact on physical activity, particularly in terms of neighborhood walkability and active commuting levels (Ellis, et al. 2016). Also, in the research, significant relationships between the two combinations of smoking and drinking, and obesity and inactivity have been pointed out, and there is significant evidence that there is a relationship between smoking and alcohol consumption, obesity, and sedentary behaviors (Daw, et al. 2017).

According to the mentioned studies, the classification of spatial factors related to obesity in this article can be generally divided into three categories: access to food environment, access to physical activities and access to smoking & drinking centers.

3. Theoretical Framework

Making unhealthy food decisions depends on several factors, including environmental accessibility (availability and accessibility of unhealthy food in the environment) and internal factors (food preferences). The built environment ensures the availability and access to food for citizens. Distance to the grocery store (is it accessible on foot or is transportation required?), proximity to fast-food outlets, access to home restaurants, and many other factors in between. People living in low-income neighborhoods rely on limited options that may lack nutrients and are often expensive. In contrast, citizens living in affluent neighborhoods have access to a wide variety of large grocery stores, affordable food choices, and fewer fast-food outlets (Marcone, et al. 2020; Drewnowski, 2012).
It is important to distinguish between different "exposures" criteria to define availability or accessibility to fast-food outlets. Accessibility refers to the number or density of fast-food outlets within predefined administrative boundaries (such as neighborhoods) or buffers around a residential address (Oexle, et al., 2015). Accessibility is often used to show geographic accessibility, measured as the distance from home or proximity to home. However, the two terms are often used interchangeably in the literature. Both accessibility and affordability provide one-dimensional views of "exposure" to the food environment. Even if fast-food outlets are available, they may not be accessible: for example, because they are not accessible or because they are not affordable (Ghosh-Dastidar et al., 2014; Gustafson, et al., 2012; Mackenbach et al., 2017). Similarly, even if the nearest fast-food restaurant is near a person's home, people may use food outlets further away, for example, because they like to vary their fast food consumption. The use of one-dimensional definitions of "exposure" to the food environment prevails, but the concept of "spatial access" has been proposed to overcome its limitations. Spatial accessibility considers both density (availability) and distance to (proximity) facilities (Hansen, 1959; Salz et al., 2011; Stewart, 1941) but is still used in studies of fast-food outlets not taken (Mackenbach, et al. 2019). Alcohol consumption, alcoholic beverages, smoking, drug use, and overeating are related to obesity; meanwhile, there is an obvious connection between smoking and alcohol consumption with obesity (Daw, et al. 2017; Shaikh, et al. 2015; Luo, et al. 2020).

The relationship between smoking and obesity is complex and not fully understood, and published studies have yielded conflicting results. While some studies have shown no significant association between smoking status (number of smokers) and body mass index (BMI) (Zbikowski, et al. 2011), others have suggested that smoking may be associated with lower BMI (Klesges, et al. 1989) and smoking cessation is associated with increased BMI (Munafò, et al. 2009). Also, several studies have shown that smoking behavior is closely related to body weight and the incidence of obesity (Albanes, et al. 1987; Filozof, et al. 2004) and showed that people who smoked were heavier than people who did not have ever been smokers (Flegal, et al. 1995; Mackay, et al. 2013). It is possible that this relationship reflects an inverse factor since overweight individuals who are trying to lose weight are likely to be more motivated to start smoking (Chiolero, et al. 2008). Mechanisms underlying the effect of smoking on weight include energy intake, physical activity, metabolic rate, and inflammatory status associated with smoking status (Albanes, et al. 1987). However, previous studies have also investigated possible causal mechanisms. The strongest evidence, to date, has pointed to the effect of cigarette nicotine on reducing obesity (Wack & Rodin, 1982; Chiolero, et al. 2008; Dare, et al. 2015). Unadjusted analysis showed that the BMI of smokers, regardless of the smoking method, was significantly higher compared to never-smokers (p < 0.001). Moreover, 83.3% of waterpipe (WP) smokers, 76.5% of cigarette smokers, and 75.4% of dual smokers were either overweight or obese compared to 49% in the never smokers group (Alkeilani, et al. 2022).
Table 1
Type of independent variables

<table>
<thead>
<tr>
<th>Conceptual classification</th>
<th>Reference</th>
<th>Variables obtained from the Australian Statistical Information Center</th>
<th>Type of index</th>
<th>Name of analysis method</th>
</tr>
</thead>
<tbody>
<tr>
<td>eating habits (fastfoods)</td>
<td>accessibility to food centres, and the number of times eating out</td>
<td>(Marcone, et al. 2020); (Raine, 2005); (Witchell &amp; Sheenka, 2011)</td>
<td>Café</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Juice bar</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Restaurant</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Restaurant café</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Fast food</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Food court</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Restaurant bar</td>
<td></td>
</tr>
<tr>
<td>smoking, drinking alcohol</td>
<td>access to entertainment centres and spending recreation</td>
<td>(Dare, et al. 2015)</td>
<td>Leisure</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Smoking area</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Winery</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Pub</td>
<td></td>
</tr>
<tr>
<td>Physical activity</td>
<td>the possibility of movement and active mobility</td>
<td>(Cereijo, et al. 2022)</td>
<td>Exercise</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(Slater, et al. 2019)</td>
<td>Gym</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Bicycle parking</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Bicycle renter</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Foot Street</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>pedestrian way</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Active travel</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>behaviour</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Park</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Open space</td>
<td></td>
</tr>
</tbody>
</table>

Local parks and fitness facilities (e.g., health clubs, gyms, YMCAs) may help facilitate physical activity and support obesity prevention efforts. Previous research has linked living in an area with greater access to recreational facilities such as parks and fitness facilities with greater physical activity and healthier body weight (Slater, et al. 2016; Slater, et al. 2013; Slater, et al. 2010; Powell, et al. 2007; Adams, et al. 2015; Dumbaugh & Frank 2015). Public parks or open spaces may be most used in the context of physical activity (Cohen, et al. 2007; Giles-Corti B & Donovan, 2002), and access to these resources in neighborhoods depends on socio-economic characteristics and urban characteristics (Jones, et al. 2015; Wen, et al. 2013; Powell, et al. 2006).

Neighborhood characteristics (e.g. parks, green spaces, physical activity facilities) are important determinants of physical activity (Diez Roux & Mair 2010; Olabarria, et al. 2014), especially in more deprived neighborhoods (Grundmann, et al. 2014; Gaskin, et al. 2014). Increasing access to places for physical activity such as parks, along with other built environmental changes, is critical to preventing obesity in the entire population (Department of Health and Human Services, 2015; Slater, et al. 2019). The conceptual framework of this article extracts from the literature review is as follows (Fig. 1):

4. Data And Methodology
4.1. Data

Melbourne is the case study of this article. The city has 309 SA2 census blocks at the medium level. Therefore, all data are pooled for different variables and modeling purposes. The unit of analysis is SA2. Ease of access to data at this level is among the factors for choosing it as the basis for data collection. This data is from the latest Australian census, which is updated annually in 2023. The explanatory variables used in this article are a continuous combination of socioeconomic structure aspects extracted from the population and housing census of GMA in 2016 and the spatial variables of number (Availability) and distance (Accessibility) of urban activities extracted from POI (Point Of Interest). It is believed that their spatial changes can affect the changes in levels of obesity in SA2 Melbourne. Only the most influential components were selected when examining the collinearity between the analyzed variables. For this purpose, the variance inflation factor (VIF) is used. Table 2 explains the statistically significant components and their descriptive statistics.

Table 2
Descriptive statistics of key variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Range</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent</td>
<td>Obesity</td>
<td>23.03</td>
<td>21.18</td>
<td>4.24</td>
<td>0.00</td>
<td>-0.27</td>
<td>-</td>
</tr>
<tr>
<td>Intervening</td>
<td>SEIFA</td>
<td>10</td>
<td>6.5</td>
<td>2.77</td>
<td>-0.64</td>
<td>-0.67</td>
<td>1</td>
</tr>
<tr>
<td>Independent</td>
<td>Distance to Food Center (Accessibility)</td>
<td>14720.64</td>
<td>978.66</td>
<td>1467.54</td>
<td>4.76</td>
<td>31.62</td>
<td>1.22</td>
</tr>
<tr>
<td></td>
<td>Exercise Center (Accessibility)</td>
<td>20426.23</td>
<td>2339.74</td>
<td>3388.50</td>
<td>3.32</td>
<td>12.32</td>
<td>1.23</td>
</tr>
<tr>
<td></td>
<td>Smoking Center (Accessibility)</td>
<td>17812.27</td>
<td>2739.05</td>
<td>2511.78</td>
<td>2.04</td>
<td>6.54</td>
<td>1.38</td>
</tr>
<tr>
<td>Number of</td>
<td>Food Center (Availability)</td>
<td>702.00</td>
<td>20.97</td>
<td>45.71</td>
<td>11.19</td>
<td>161.04</td>
<td>2.16</td>
</tr>
<tr>
<td></td>
<td>Exercise Center (Availability)</td>
<td>136.00</td>
<td>6.75</td>
<td>17.02</td>
<td>4.63</td>
<td>24.98</td>
<td>1.51</td>
</tr>
<tr>
<td></td>
<td>Smoking Center (Availability)</td>
<td>38.00</td>
<td>1.32</td>
<td>3.23</td>
<td>6.52</td>
<td>59.72</td>
<td>1.72</td>
</tr>
</tbody>
</table>

N = 309

4.2. Methodology

The method of this research examines the relationship between the obesity phenomenon and spatial access in GMA in three parts. This research analyzes the spatial distribution of physical activity centers, food centers, and cigarette and liquor centers by using two indicators of accessibility and availability, and in this way, it uses the following methods:
Nearest Neighbor Index NNI

Point pattern analysis is commonly used to reveal the spatial distribution of research objects by evaluating the spatial location of point events. Usually, the nearest neighbor index (NNI) method, which is based on distance are used to analyze the spatial distribution of research point entities from accessibility. NNI compares the deviation of specific distributions from the random distribution by calculating the ratio of the average distance of the nearest neighbor pair to the average distance in the random distribution model as follows (Eq. 1):

\[
NNI = \frac{\sum^N_{i=1} \frac{\min(d_{ij})}{N}}{0.5\sqrt{\frac{d}{S}}}
\]

Eq. 1

Where \( \min(d_{ij}) \) is the distance between any point and its nearest neighbor, \( n \) is the total number of beautiful leisure villages, and is the study area (Li, et al., 2019).

Kernel Density Estimation (Availability)

Kernel density estimation (KDE) method, which is based on density, are used to analyze the spatial distribution of research point entities from availability. The KED density equation can be described as follows (Eq. 2):

\[
f_n(x) = \frac{1}{nh^d} \sum^n_{i=1} k \left( \frac{x - x_i}{h} \right)
\]

Eq. 2

where \( K(x-x_i/h) \) is the kernel density equation, \( x_i \) is the kernel density of each point, \( x \) is the kernel density at the center of the grid, \( h \) is the threshold, \( n \) is the number of points within the threshold range, and \( D \) is the dimension of the data. Its geometric function requires that the density at the center of each \( x_i \) point is the highest and that this decreases as the points move away from the center. When the distance from the center reaches a certain threshold value (the edge of the window), the density is zero, and the core density at the grid center \( x \) is the sum of the densities within the threshold range (Liao, et al. 2022).

Local Moran's I

In addition to the general Moran index, there is also the local Moran index, which is used to determine the location of clusters. Moran's local statistics explain the pattern of the spatial relation of a spatial parameter in the neighborhood. In other words, this statistic determines the degree of autocorrelation between the adjacent cell values in a geographical area and tests its significance. Its calculation formula is similar to the regression formula where there are two variables \( x \) and \( y \), and the autocorrelation between them is calculated, so the difference of each variable from the mean is obtained. However, here \( x \) and \( y \) are a point and its neighbor; in fact, we use neighbors as well. The local Moran index is considered according to Eq. (3). In this respect, the matrix \( w \) is a proximity matrix that is considered to be a neighbor and adjacent if the number is 1 and not adjacent if the number is 0. The local Moran index is distinct from its general index and is calculated for each cell as follows (Eq. 3):

\[
I_i = \frac{\sum^n_{j=1, j \neq i} w_{ij} (x_i - \bar{X})}{\sum^n_{j=1} w_{ij} \sum^n_{j=1} w_{ij} X^2}
\]

Eq. 3

In Eq. (3), \( x_i \) is a value for feature \( i \), \( X \) is the mean of the descriptive values, \( w_{ij} \) is the spatial weight between two features \( i \) and \( j \) where the sum of weights is 1, and \( n \) is the total number of features (Ghodousi, et al. 2020). This method is important for identifying spatial association patterns because it can identify smaller geographic areas where positive or negative clustering occurs. Values range from -1 to +1, and a value of 0 indicates no spatial correlation. Positive values indicate positive spatial correlation and negative values mean inverse correlation. The hypothesis tests of this method are significant at the 95% confidence level (P-value < 0.05) and show the importance of the results.

The HH means that the identified locations have high index values and are close to other areas of high value, the LL value means that areas identified with low values are surrounded by areas with low values, the LH value represents areas with a low value surrounded by other areas with high values, while HL is the opposite, they are regions with high values close to locations with low values. HH values were red-colored, LL blue-colored; LH light blue-colored and HL light red-colored (de Araújo Morais, 2021).
GWR

As an optimized spatial analysis method, Geographic Weighted Regression (GWR) is a powerful tool for exploring the spatial relationship between variables by establishing the local regression equation for each spatial location. In a sense, GWR is a refined moving windows approach where observations within the windows are weighted based on distance from the regression point, rather than evaluated equally as in moving windows regression. The GWR method embeds spatial location in the regression parameters and considers local parameter estimates. Instead of estimating global parameter values, by estimating the parameters at each location GWR generates a continuous surface of spatially varying parameter values. Mathematically, the GWR is a linear regression model as follows (Eq. 4):

\[ y_i = \beta_0 (u_i, v_i) + \sum_{k=1}^{P} \beta_k (u_i, v_i) x_{ik} + \epsilon_i \quad i = 1, 2, 3,..., n \quad \text{Eq. 4} \]

Where \((u_i, v_i)\) are the spatial coordinates of each sample point \(i\), \(\beta_0 (u_i, v_i)\) is the intercept of sample \(i\), \(\beta_k (u_i, v_i)\) is the regression coefficient of sample point \(i\), \(x_{ik}\) is an observation of the \(k\)th environmental variable of sample \(i\), \(y_i\) is the fitting value of Cd content at sample point \(i\) and \(\epsilon_i\) is the random error. If \(\beta_1 = \beta_2 = \ldots = \beta_n\), the GWR method reduces to the earlier OLS model (Chen, et al. 2022; Ma, et al. 2021).

5. Findings

Bivariate

Examining the spatial distribution of SEIFA and obesity in SA2 blocks shows that as you get closer to the center of GMA, the SEIFA index increases and obesity decreases. This is despite the fact that this issue has the opposite conditions in the outer areas; in a way that in SA2 outer of Melbourne, we are faced with a decrease in SEIFA and an increase in obesity (Fig. 2). This issue can be proven in the ANOVA test so that for all SA2s, the relationship between SEIFA and obesity has Significance \(< 0.05\), VIF \(< 7\) and T-Statistic \(< 0\), and this means the opposite relationship between these two variables.

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
<td>Tolerance</td>
</tr>
<tr>
<td>1</td>
<td>(Constant)</td>
<td>25.277</td>
<td>.561</td>
<td>-</td>
<td>45.027</td>
</tr>
<tr>
<td>SEIFA</td>
<td>- .630</td>
<td>.079</td>
<td>-.413</td>
<td>-7.937</td>
<td>.000</td>
</tr>
</tbody>
</table>

Dependent Variable: Obesity

\(R^2 = 0.42\)

\(F = 63\)

\(N = 309\)

According to Table 3 and the division of SEIFA areas into High and Low areas, it can be said that in 309 blocks of SA2, in general, the lower the SEIFA and the disadvantaged SA2, the more obesity we face, and the higher the SEIFA and the advantaged SA2, the less obesity is seen. This issue has been addressed in some studies and they show that the socioeconomic status of neighborhoods is related to obesity as one of the consequences of individual health (Fan, et al. 2020; Hanson, et al. 2021; Kerr, et al. 2021).

Local Moran’s I

Based on the clustering map obtained from the Local Moran’s I index in this research, among 309 GMA blocks, 188 blocks have a significant relationship between obesity and the SEIFA index (P-Value \(< 0.05\)). The result of this model in Fig. 4 shows that 96 blocks have low obesity and high SEIFA (advantage), and 85 blocks have high obesity and low SEIFA (disadvantage); because of the significant number of SA2 blocks of these two clusters, have a more appropriate statistical analysis capability. As shown in Fig. 4. Obviously, the number of blocks with low obesity and high SEIFA index is more than other blocks. Also, the blocks with high obesity and low SEIFA had a significant proportion that is in GMA malnourished areas.
Despite the influence of individual behaviors on the occurrence of obesity, the physical and social environment of the city has a great impact on the occurrence of obesity, for example, the dispersion of services, access to healthy food, access to sports, and the social environment in the neighborhood influence the incidence of obesity (Congdon, 2019). As a result, in order to find the relationship between obesity and the SEIFA index, in this research, we focused on two regions, High-Low and Low-High, which are meaningfully opposite. In this part of the analysis, the relationship between the three variables of physical activity centers, food centers, and drinking and smoking centers in High-Low and Low-High areas have been investigated by using two indicators of accessibility and availability.

Examining the distance threshold of changes in the share of obese people with respect to the three independent variables of FoodD, ExerciseD and SmokingD in the Low-High and High-Low clusters includes the following results:

In the Low-High cluster with emphasis on low obesity rate and high SEIFA, SA2s, which have more obesity in the range of less than 20% average than other areas, are less than 1000 meters away from food centers. Also, they are less than 2000 meters away from physical activity centers and less than 3000 meters away from smoking and alcohol centers.

In the High-Low cluster, with emphasis on high obesity rate and low SEIFA, SA2s, which have more obesity than other regions in the range of more than 20%, are less than 2000 meters away from food centers. These areas are less than 5000 meters away from physical activity centers and less than 7500 meters away from smoking and alcohol centers.

Based on the results from Fig. 5 in general, the increasing changes in the share of obese people, especially the SA2s of the Low-High cluster, can be attributed to the 200% increase in the distance to food centers. Also, the 250% increase in the distance to the physical activity centers and the 250% increase in the distance to the cigarette and alcohol centers in the High-Low cluster (with low SEIFA) compared to the Low-High cluster can be seen as other reasons for this issue. In the following, this article will be examined in detail based on spatial analysis.

Explanatory Regression between Nearest Neighbor Index NNI (Distance) & Kernel Density Estimation (Number) with obesity

Examining the correlation model of availability and accessibility of the three variables Exercise, Smoking, and Food in two meaningful clusters, High-Low and Low-High, shows the following results:

In the Low-High cluster, ExerciseD (P-Value = 0.01) and FoodD (P-Value = 0.05) have a positive relationship with the share of people with BMI > 30, while the variable SmokingD (P-Value = 0.05) has a negative relationship with the dependent variable. In the High-Low cluster, the variables ExerciseD, and FoodD both have a positive relationship with the share of people with BMI > 30 with P-Value = 0.05 (Table 5), which can also be seen in the Low-High cluster. In this cluster, like the Low-High cluster, the SmokingD variable with P-Value = 0.05 has a negative relationship with the share of people with BMI > 30 (Table 4). In both clusters, the significance of the variables that are related to distance and somehow indicate the accessibility status of these variables indicates that these variables are the most important than the number of variables that are related to the availability status.

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Summary of Spatial Autocorrelation (SA) HighLow</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster Type</td>
<td>SA</td>
</tr>
<tr>
<td>X1</td>
<td>X2</td>
</tr>
<tr>
<td>LowHigh</td>
<td>0.00</td>
</tr>
<tr>
<td>0.00</td>
<td>490.80</td>
</tr>
<tr>
<td>0.00</td>
<td>491.13</td>
</tr>
<tr>
<td>HighLow</td>
<td>0.00</td>
</tr>
<tr>
<td>0.00</td>
<td>462.24</td>
</tr>
<tr>
<td>0.00</td>
<td>466.68</td>
</tr>
<tr>
<td>Model Variable significance (P-Value): * = 0.10; ** = 0.05; *** = 0.01</td>
<td></td>
</tr>
</tbody>
</table>
GWR

Analysis of the spatial relationship between obesity and the built environment, including food centers, physical activity centers, and smoking and alcohol centers, which, based on theoretical literature, have an important effect on obesity changes, using the GWR model in two indicators of availability and accessibility in GMA, the result It shows:

According to the results of the spatial analysis of the GWR model, as shown in Table 6, the Low-High cluster is significantly more important than the High-Low cluster; because its R2 index is 0.75 against 0.13 of the High-Low cluster. This means that in the Low-High cluster, the significance of 75% of the independent variables compared to the dependent variables can be proven. This amount for the High-Low cluster is 13%. It should be noted that although the significance level of the High-Low cluster is lower than the Low-High cluster, it is significant and analyzable according to the P-Value < 0.05 resulting from the analysis based on Local Moran's I (Figs. 3 and 4).

<table>
<thead>
<tr>
<th>VarName</th>
<th>Variable</th>
<th>High-Low</th>
<th>Low-High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth</td>
<td></td>
<td>864784.47</td>
<td>5819.70</td>
</tr>
<tr>
<td>ResidualSquares</td>
<td></td>
<td>1035.63</td>
<td>259.82</td>
</tr>
<tr>
<td>EffectiveNumber</td>
<td></td>
<td>4.01</td>
<td>35.47</td>
</tr>
<tr>
<td>Sigma</td>
<td></td>
<td>3.57</td>
<td>2.07</td>
</tr>
<tr>
<td>AICc</td>
<td></td>
<td>464.50</td>
<td>446.09</td>
</tr>
<tr>
<td>R2</td>
<td></td>
<td>0.13</td>
<td>0.75</td>
</tr>
<tr>
<td>R2Adjusted</td>
<td></td>
<td>0.10</td>
<td>0.61</td>
</tr>
<tr>
<td>Dependent</td>
<td>Obesity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Independent</td>
<td>FoodD, ExerciseD, SmokingD</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Indicators of the built environment have significant effects on obesity, as well as malnutrition and the level of access to facilities influence the occurrence of obesity, and this confirms the importance of access to sports facilities, activity levels, and dependence on cars in traffic in the occurrence of obesity (Congdon, 2017). As a result, in the continuation of this research, to analyze the relationship between the built environment and obesity, by using two indicators of accessibility and availability to urban activities, the relationship between each of the activity centers and obesity was analyzed:

According to the output of Fig. 5-D, it was found that the more access to food centers in the more privileged areas (high SEIFA), the less obesity; This shows that although in the category of food center activities, we are faced with an increase in access to bars, fast food, restaurants and cafes in the region, the quality of food offered in this region has led to a reduction in obesity, an issue that is common in low-income areas (Low SEIFA) did not show a significant relationship (Fig. 6). To further prove this relationship, we can refer to studies that have focused on the issue of food deserts (Widener, 2018; Smets, Cant & Vandevijvere, 2022). Food deserts specifically focus on the quality of food available and the type of access residents have to these basic food needs. Food deserts have a great impact on poor regions and minorities and consider food and health costs as very important components (Bellian, 2019). In the example of food deserts in food insecure areas in Fig. 6, it can be recognized that there is no relationship between accessibility to food centers and obesity reduction.

There is a direct significant relationship between the accessibility of physical activity spaces and obesity. It should be noted that the most significant relationship among all three activities investigated in this research is related to this section. The result of this test shows that the shorter the distance from sports centers, the less obesity (Fig. 6-B). It should be noted that the issue of access to physical activity spaces and its effect on reducing obesity has been mentioned and confirmed in many studies; For example, proximity to green spaces can stimulate physical activity and thus reduce obesity (De la Fuente, et al. 2021), however, fewer studies
have linked this issue to the social and economic characteristics of neighborhoods. This issue was clearly evident in the case of the two rich and poor regions in this research, as shown in Fig. 5 due to the shorter distance between sports centers in the rich region according to SEIFA, the obesity rate is lower, and also in the poor regions of Melbourne city due to the greater distance between sports centers compared to In privileged areas, obesity is higher. The issue is clear in graph number 2 and in the comparison between the LGAs of the city of Melbourne. Thus, the effects of the local built environment on obesity status may be greater in people living in areas with lower socioeconomic indicators, because their activity spaces (i.e., the areas they use for their daily activities) are typically more limited than the activity space. People who live in areas with higher socioeconomic conditions (SEIFA) and this leads to a greater dependence on the direct effect of the neighborhood environment on obesity (Mackenbach, et al. 2019).

Examining the relationship between the accessibility of smoking and alcohol centers with obesity, based on the GWR spatial classification, shows that in SEIFA clusters, both in SA2s that have good conditions and in SA2s that have poor conditions, there is little difference in the relationship between the distance of SA2s from smoking and alcohol centers. It does not exist, because, in both clusters, most SA2s are close to these centers. But the changes in obesity in these two clusters are opposite to each other, in a way that in Low-High areas, by reducing the distance of SA2s to smoking and alcohol centers, the obesity rate decreases, but in High-Low areas, by reducing the distance of SA2s to these centers, the obesity rate increases. This relationship confirms the effect of smoking and alcohol consumption because of its accessibility for people on the increase of obesity.

Conclusion And Discussion

Analyzing the spatial distribution patterns of the share of obese people is necessary for several reasons and may help us create prevention strategies that aim to improve people's health and distribute resources more effectively by increasing accessibility to centers of physical activity and optimal nutrition. Reducing the accessibility to smoking and alcohol centers and undesirable food will ensure the health of local communities. In this way, state and local governments may promote healthier and more prosperous neighborhoods and minimize obesity-related morbidity and mortality by analyzing the distribution patterns of obesity-influencing activity centers in the GMA.

We conducted this study on 309 blocks in GMA in order to investigate the relationship between obesity and the indicators of accessibility and availability to the activities of food centers, physical activity centers, and smoking and alcohol centers, in the significant clusters of SEIFA. Our study is the first study that examines the two indicators of accessibility and availability (spatial access) to activities and facilities and the association of obesity through the influence of social and economic characteristics of neighborhoods at the city level. We found that in terms of non-spatial correlation analysis, the changes in obesity rates in both SEIFA clusters have a negative relationship with the distance from smoking and drinking centers and also have a positive relationship with food centers and physical activities. Meanwhile, in terms of spatial correlation analysis, the benefits of placing activities in SA2s close to the center of GMA (high SEIFA) and those in inner and outer SA2s (low SEIFA) in Melbourne change the direction of the correlation between obesity and access to centers. The three centers of activity in this article are effective. In such a way that access to food centers has a positive relationship in non-spatial analysis conditions, but in spatial analysis conditions, it has a negative relationship in Low-High areas and a positive relationship in High-Low areas. Regarding access to physical activity centers, we see a positive relationship in both spatial and non-spatial analysis modes. In relation to access to smoking and alcohol centers, although there is a negative relationship in terms of explanatory regression in both SEIFA clusters, spatially in the SA2s center of the GMA area, which has high SEIFA conditions, there is a positive relationship, and in other SA2s, there is a negative relationship.
<table>
<thead>
<tr>
<th>Type of Clustering</th>
<th>Variables</th>
<th>Coefficient of Explanatory Regression (Non-Spatial Regression)</th>
<th>Coefficient of GWR (Spatial Regression)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-High</td>
<td>FoodD</td>
<td>+ (All SA2s)</td>
<td>- (Center)</td>
</tr>
<tr>
<td></td>
<td>ExerciseD</td>
<td>+ (All SA2s)</td>
<td>+ (Center)</td>
</tr>
<tr>
<td></td>
<td>SmokingD</td>
<td>- (All SA2s)</td>
<td>+ (Center)</td>
</tr>
<tr>
<td>High-Low</td>
<td>FoodD</td>
<td>+ (All SA2s)</td>
<td>+ (Inner &amp; Outer)</td>
</tr>
<tr>
<td></td>
<td>ExerciseD</td>
<td>+ (All SA2s)</td>
<td>+ (Inner &amp; Outer)</td>
</tr>
<tr>
<td></td>
<td>SmokingD</td>
<td>- (All SA2s)</td>
<td>- (Inner &amp; Outer)</td>
</tr>
</tbody>
</table>

These results are consistent with previous studies that found obesity to be more common among residents living in areas with fewer available amenities and activities. Importantly, we found that the association between the level of accessibility to activity centers and the prevalence of obesity was largely attenuated after the intervention of economic and social characteristics of neighborhoods in SA2. This issue has two important results. First, it shows that the socio-economic conditions of each SA2 in the prevalence of obesity may be analyzed and then controlled by different distribution of activity centers in SA2s. An obvious example to express this connection is the increase in accessibility to physical activity.

Second, these patterns show that the areas with the highest prevalence of obesity are the areas characterized by low economic and social characteristics and the lowest accessibility to food centers and physical activity.

Also, in the analysis of the spatial relationship between the activities and centers of smoking and drinking obesity increased with the increase of accessibility to these centers. This issue was shared between the High-Low and Low-High clusters and confirmed the relationship between alcohol consumption and smoking and increasing obesity due to increased accessibility to these centers.

The results of Fig. 7 show the relationship between the dependent variable (the proportion of people with BMI > 30) and the significant independent variables (FoodD, ExerciseD, and SmokingD) in a three-dimensional diagram in two clusters Low-High (Fig. 7 - Right) and High-Low (Fig. 7 - Left) shows that:

In the Low-High cluster, focusing on high SEIFA, the SA2s with the lowest obesity rates, such as Malvern East, Burwood, Balween, Box Hill, are less far from food centers and more from smoking and alcohol centers. Also, SA2s such as Surry Hills, Burwood East, and Malvern are less far from physical activity centers and more from smoking and alcohol centers. Armadale, Kew, Brighton, and Brighton East, which have the lowest obesity rate, are located at a shorter distance from food centers and physical activity centers. Accordingly, in the Low-High cluster, short distances from physical activity centers, long distances from smoking and alcoholic beverage centers, and short distances from food centers play an essential role in low obesity.

In the High-Low cluster focusing on high obesity and low SEIFA, the SA2s with the highest obesity rates of Broadmeadows, Meadow Heights, Keilor Downs, and Kings Park are less far from smoking and alcohol outlets and more from food outlets. Also, SA2s such as Frankston North, Whittlesea, Melton South, and Sunbury are at a greater distance from physical activity centers and less from food centers. Rockbank, Campbellfield, and Tullamarine, which have high obesity, are located at a greater distance from physical activity centers and more from smoking centers. Accordingly, in the High-Low cluster, a long distance from physical activity centers, a short distance from smoking and alcoholic beverage centers, and a short distance from food centers play an essential role in low obesity.

The relationship of the short distance from food centers (including fast food centers) in both High-Low and Low-High modes means that access to these centers in a neighborhood alone cannot be the cause of increasing and decreasing obesity and this index in Combination with other indicators such as income, lifestyle, etc. can affect changes in obesity.

The strength of this study includes two important dimensions:

First, this research examined the economic and social characteristics of SA2s in relation to obesity and its prevalence and introduced the accessibility of activities and restrictions on them as one of the main indicators of the prevalence of obesity in residential
contexts. In other words, so far no study has investigated this relationship spatially, for example, most studies use objective measures of accessibility and proximity to fast-food outlets, such as those provided by GIS tools provided (Fraser et al., 2010). Therefore, in this research, for a more spatial evaluation, special attention was paid to SEIFA indicators (advantaged and disadvantaged SA2s) and its mediating role in the level of accessibility to activity centers was emphasized. For example, the existing activities such as fast food centers in the advantaged areas of Melbourne will provide healthier and higher quality and therefore more expensive food distribution than the deprived areas, which can negate the relationship between obesity and fast food centers.

Second, this study examined all significant blocks of the city of Melbourne (309 blocks), covering over 70% of Melbourne’s population, the breadth of this statistical volume minimized selection and analysis bias and allowed us to record spatial diversity in a city. The diagnosis of obesity in advantaged and disadvantaged areas was highly reliable by using the SEIFA index and the population and housing census data regarding in SA2 level, and the distribution of obesity and activity centers were clearly classified.

Studying obesity distribution patterns in Melbourne can be very beneficial for policy-making and urban planning. Government and policymakers can use the results to develop evidence-based interventions that are tailored to the specific needs of different regions in SA2s. Similarly, this research identified specific social and economic clusters that are at greater risk of obesity. Policymakers can use this information to develop interventions that address the specific needs of those groups based on the distribution of activity centers and increase the level of accessibility. Planners can use the results to inform land use decisions in order to guide decisions about the location of future developments, especially activity centers that affect the health of local communities (Gullon, et al. 2021). These findings have potential policy implications because they show that the accessibility of these activity centers affects the advantages and disadvantages of SA2s.

References


**Figures**
Figure 1
The conceptual framework

Figure 2

A: BMI≥30
B: SEIFA
C: Overlay
The spatial relationship between SEIFA variable and BMI≥30

Figure 3
P-Value of significance relationship between Obesity and SEIFA

Figure 4
BILISA Cluster Msp based on MORAN`s I
Figure 5

distance threshold of changes in the share of obese people with respect to the three independent variables of FoodD, ExerciseD and SmokingD
Figure 6

GWR Maps
Figure 7

Relationship between Obesity and FoodD, ExerciseD and SmokingD in a three-dimensional diagram in Low-High cluster (Right) and High-Low cluster (Left)