Are Londoners Getting Healthier?

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Keywords: Obesity, Mental Health, London, Spatial Pattern.

Abstract: It utilised urban data from multiple sources, to map out the physical health and mental health patterns in London over space and time. On basis of recognising the spatial patterns trajectory changes, obesity among adults and children in London areas had been investigated with selected demographic, socio-economic and environmental factors, to identify the most influential factors in all, and for local community; similarly, workflow had been again designed to investigate the influential factors for mental health prevalence as well. Upon comparing the selected models, models considering neighbourhood spillover effect has been found to be the optimal, to identify significantly influential factors on urban health, such as age group, green space access, household deprivation, income deprivation and air quality. The findings underscore the necessity for targeted, location-specific public health interventions to effectively combat obesity; highlight the importance of spatial heterogeneity, offering detailed insights into regional variations; and suggest tailored strategies for public health policies. This work fills a critical gap and demonstrates the need for geographically informed public health strategies.

1 INTRODUCTION

As the capital of UK, health statuses for London residents have always been the prime topic, and could be interpreted from mainly two strands, the physical health and the mental health. The former strand has been found to be with “overweight and obesity represent probably the most widespread threat” to physical health (Department of Health and Social Care, 2011), requiring for leaders’ implementing public health measures to reduce obesity, such as the Mayor’s London Food Strategy to tackle with obesity and provide a framework for assessing the impact of these policies (PHE, 2020). The latter strand is a crucial component of human being’s overall well-being and is closely linked to physical health (NHS England, 2020), hence organisations such as PHE and the GLA regularly publish reports and datasets that for further investigations (Rosenberg, 2019). It also inspired empirical studies investigate the significant socioeconomic disparities among London, suggesting influential socioeconomic factors may drive the disparities among London regions (Mayor of London, 2018). However, there is a lack of evidence on status quo patterns of Londoners’ health: are they becoming healthier over time? Are there any regional variations for London residents’ health statuses, for either physical health or mental health? If so, what are the influential factors driving such differences?

To address above questions, this project aims to explore the latest obesity and mental health levels among London residents, on basis of multiple openly accessed datasets from varied sources, to map out the health spatial patterns changes in London in recent decade by age group, to investigate the driving forces from socio-economic contexts and environmental measures, so to serve the potential strategic policy adjustments among relevant stakeholders for healthcare equity and improvement in the city.

2 BACKGROUND AND EMPIRICAL STUDIES

2.1 London Demographics

London is formed by City of London and other 32 boroughs, further breakdown into 417 Middle layer Super Output Areas (MSOAs) or 4835 Lower Super Output Areas (LSOA) (ONS, 2011), with residents

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Li, Y., Tan, S., Chang, X. and Chen, X.
Are Londoners Getting Healthier?.
DOI: 10.5220/0013203300003935

In *Proceedings of the 11th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2025)*, pages 15-26
ISBN: 978-989-758-741-2; ISSN: 2184-500X

around 8.9 million (ONS Census 2021, 2022), and is well-known for its ethnic and cultural diversity in that, residents in London speak more than 300 languages and come from a wide range of ethnic backgrounds (GLA, 2020). High level of population diversity brings the mayor's manifesto commitment on a "fairer, healthier and more equal" London (Mayor's Office, 2022) become a prominent but challenging topic, hereafter the necessity to understand Londoners' status quo health levels.

2.2 Obesity as a Measure for Physical Health

As defined by WHO (2024), obesity is the excessive accumulation of fat that poses a threat to health, which commonly measured by body mass index (BMI), where people with higher BMI may expose to higher risk of obesity-related health complications. From WHO's classification, adults with obesity are normally categorised into Grade I obesity (BMI at 30-34.9), Grade II obesity (BMI at 35-39.9), and Grade III obesity (also known as morbid obesity, BMI at 40 or above); children's obesity is defined by age-specific BMI percentiles at or above the 95th percentile for their age and sex.

Individuals diagnosed with obesity were related to potential health problems by their age groups, stages of growth and development. For example, children are normally thought to experience high metabolic rate and rapid physical and psychological changes (Stamatakis et al., 2010), with potentially long-term health influences into their adulthood. On the contrary, adults have a relatively lower metabolic rate and a mature lifestyle and eating habits, hence obesity developed during adulthood will be associated with chronic diseases such as heart disease and diabetes. Their living environments are taken as influential to the development of obesity symptoms. For instance, access to recreational facilities, availability of healthy food, transport infrastructure, and the built environment are important shaping residents' lifestyles, then affect local obesity rates. The city's extensive public transport network, abundant green spaces and walkability create a unique environment for assessing the impact of urban design on physical activity levels and eating habits (ONS, 2019). Recent research on adult obesity has highlighted the complex interplay of multiple influencing factors, including socioeconomic status, dietary habits, physical activity, and environmental conditions. Stafford et al. (2010) enriches this discussion by highlighting that, obesity trends are severe among population from poorer socioeconomic backgrounds in developed countries. For example, people with lower incomes may face food insecurity, leading to poorer diet quality and higher rates of obesity. These findings reflect the broader claim that, socioeconomic disadvantage is a key determinant of health disparities. Focusing on environmental factors, Shenassa et al. (2006) highlighted the significant correlation between sedentary lifestyles and obesity in Europe. Hobbs (2022) emphasized the impact of the environment on the level of physical exercise, which in turn affects the management of obesity, thus showing the importance of public space and parks. Furthermore, as highlighted by the 2018's Health Survey for England (NHS England, 2019), the availability of physical activity facilities versus fast food options illustrates the environmental opportunities and risks that contribute to obesity. These environmental determinants of obesity interact intricately with sociodemographic factors.

Children's development of obesity symptoms was found to have varied but interrelated factors from adults, which were mostly the home environment, school policies, access to recreational facilities, and nutrition education (Schratz et al., 2023). The impact of parental obesity and family eating habits is particularly strong in that, parental obesity, especially maternal obesity, greatly increases the risk of childhood obesity due to shared genetic and environmental factors (Kral and Rauh, 2010). Stafford et al. (2010) found that children from disadvantaged backgrounds, such as families from lower incomes or manual labors, are at greater risk of high obesity rates. Schools also play a vital role in tackling with childhood obesity in that, schools that promote physical activity and provide healthy meal choices can encourage children to make healthier lifestyle choices, hence greatly reduce obesity rates (Veitch et al., 2011). Public spaces such as parks with good accessibility and playgrounds with good quality of recreational facilities are vital, for maintaining a healthy weight for children since its encouragement of children's proper levels of physical activity (Van Lippevelde et al., 2012). Besides, educational programs provided by the city or local about healthy eating habits, can also effectively prevent childhood obesity and help families make informed choices about nutrition and physical activity, leading to healthier lifestyles (Story et al., 2009). NHS England (2023) 2022/23 school year report uncovered that, obesity rates were higher among children from deprived areas, for example, among Year 6 children 30.2% of children in the most deprived areas were obese, compared with 13.1% in the least deprived areas. These insights highlight the importance of national child and adolescent health programs in guiding public health policy and ensuring that resources are directed to the most affected communities. The programme's data will be crucial for developing effective health interventions and promoting healthy lifestyles among children in England.

2.3 Mental Health

On the other hand, mental health is another strand for Londoners' health issue. Chronic physical diseases increase as mental health levels decline (Yang et al., 2020). It can directly affect people's life experiences and quality of life in that, better mental health allows individuals to utilize their abilities and align with the broader values of society (Yang et al., 2006). However, it was not until the 1990s that people gradually realised the wider impacts of mental illness (Zhu et al., 2020). Mental health is defined as a state of well-being where individuals recognize their own abilities, can handle daily life stresses, works productively, and contributes to society (Daghagh et al., 2019). Mental health consists of the hedonic dimension, which focuses on well-being, fulfilment, and avoidance of pain, and the eudaimonic dimension, which includes personal growth, personal objectives, and mental functioning (Henderson and Knight, 2012; Ryan and Deci, 2001). The Public Health Agency of Canada (PHAC) defines mental health as the capabilities that every person possesses that enable them to experience emotions, think critically, and behave in ways that enhance their life enjoyment and their capacity to cope with challenges (Heather et al., 2017), especially in that, positive emotional and mental health that values the importance of culture, fairness, social equality, interconnectedness, and individual dignity (Heather et al., 2017).

To better measure citizens' mental health, Keyes (2002) proposed the "Mental Health Continuum" (MHC) model comprises of emotional well-being, psychological wellbeing, and social well-being. Headey et al. (1993) emphasized the dimensions on such as life satisfaction, positive emotions, anxiety and depression including factors such as socioeconomic status, social support, and life events, while the uneven distribution of these factors in different geographical areas may lead to significant differences in mental health status. Dfarhud (2014) reviewed that there are two dimensions which influence people's mental health, which are endogenic factors and exogenic factors. Endogenic factors included the biological, cognitive, personality and ethical, which are challenging to be quantified, while exogenic factors, such as greeneries, are convenient factors to evaluate their influences on mental health. Markevych et al. (2017) suggested that the greenspace could enhance the interpersonal communication, relieve the pressure and protect the environment, all these advantages are generally related to the mental health. Vires et al. (2003) runs a test with 10,000 people and found that greener area benefits human's mental health, especially for the elderly and housewives. Gianfredi (2021) said that the publicly accessible greenspace in urban area has positive influence on both physical activity and mental health, and Lachowycz (2013) suggested that the greenspace area influences people potentially, even for those people do not walk in the greenspace they would feel more satisfied.

2.4 Spatial Analytics to Understand Urban Health

A comprehensive understanding of the various aspects of physical health and mental health can support better strategic policies on appropriate interventions to address areas where poor health is prevalent among London regions. In assistance of the development of geographical information system (GIS) and relevant analytical techniques, geospatial models and tools had been widely utilised in identifying the spatial patterns of obesity. For example, Sun et al. (2020) used spatial regression models, SAR and ESF, onto childhood obesity analysis and drew associations between childhood obesity prevalence and variables such as population density, race, unemployment rate, and household income. Cetateanu and Jones (2014) have used ESDA techniques to identify spatial clusters of obesity in England, on basis of Global Moran's *I* and Local Indicators of Spatial Association (LISA), they found important clusters of high rates of obesity in urban areas and low rates of obesity in rural areas, further highlighted the need for targeted public health interventions in specific regions (Anselin et al., 2006). In London, environmental factors such as socioeconomic deprivation and access to green space, has presented similar spatial clustering patterns (Gaber et al., 2024), which were suggested to be interlinked with the relationship fast-food restaurants and supermarkets on obesity rates (ESRI, 2021). Grigoroglou et al. (2019) illustrated that depression prevalence, to reflect mental health status, could be identified of their spatial clustering patterns through Moran's *I* measure.

Underweight men were found to have higher rates of anxiety disorders compared to normal-weight men and women (McLaren et al., 2008), and obese women have higher rates of mood disorders compared to normal-weight women. Daghagh Yazd et al. (2019) also agreed that female farmers suffer greater mental distress than male counterparts, and marital status is associated with poorer mental health (Daghagh et al., 2019). Houlden et al. (2019) examined the linear relationship between the amount of green space and mental health by developing a univariate ordinary least squares (OLS) regression model exploring relevant factors of mental health indices. The GWR method computes a local regression where the coefficients can vary spatially (Brunsdon et al., 1996; 1998), hence could provide a more nuanced understanding of how different factors influence mental health (SMI) in local areas, such as the work of Cruz et al. (2022) who constructed a Bayesian spatial regression model incorporating random effects applied to the log-transformed mean SMI prevalence, to offer a precise comprehending of the spatial pattern and determinants of mental health problems, in recognising that high risk of SMI was associated with unemployment, low income, low education level, and living in a high-crime area. Besides of the multifaceted nature of mental health linking to socioeconomic status, environmental factors such as greenery, air pollution, and climate also have been examined (Mueller et al., 2023; Houlden et al., 2019; Bakolis et al., 2021). The findings highlight the huge impact that climate and air quality have on the planet. In conclusion, these studies reveal the complex impact of environmental factors on obesity and mental health, highlighting the importance of further research and consideration of multiple variables.

3 DATA AND METHODOLOGY

3.1 Data

The datasets used in this study are derived from multiple open sources and integrated into the geographical boundaries for UK Census at Middle Layer Super Output Area (MSOA) and Lower Layer Super Output Area (LSOA) levels respectively. Data fusions are realised through joining into the boundaries' shapefiles by the shared MSOA or LSOA codes for following 4 datasets:

Firstly, measures for obesity and relevant socio-economic factors mainly come from MedSat data, under CC BY-SA 4.0 license and could be found at TUMMedia (data sharing service from Technical University Munich) (Šćepanović et al., 2023), includes a wide array of variables (Figure 1) such as population density, age, gender, ethnicity, religion, marital status, employment, commute to work, residence, self-reported health, language, and the index of multiple deprivation (IMD), air quality, greenery, climate, and land cover, as well as medical prescriptions data encompasses conditions such as diabetes, hypertension, asthma, depression, anxiety, opioid prescriptions, and overall total prescriptions.

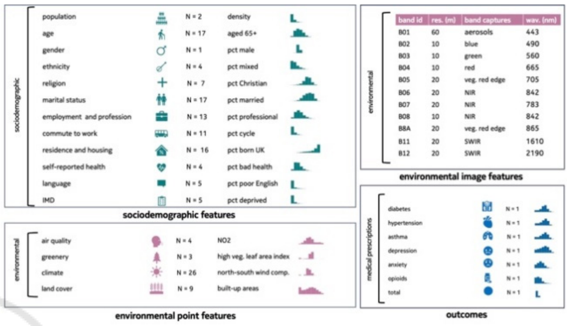

Figure 1: Structure of Medsat dataset (Access the dataset at: https://github.com/sanja7s/MedSat).

The second dataset, Access to Healthy Assets and Hazards (AHAH), is collected from the Consumer Data Research Centre (CDRC), includes a variety of variables measuring access to both healthy assets and environmental hazards, such as the distance to the nearest gambling outlet, fast food outlet, GP practice, hospital, dentist, pharmacy, and leisure center, as well as measures of air quality (nitrogen dioxide, particulate matter) and green/blue space (NDVI value for passive green space), which were collocated from various national organizations such as ONS, NHS England, NHS Scotland, LDC, DEFRA, and OpenStreetMap (Figure 2).

The third dataset on adults and children obesity is sourced from the NHS Digital's Quality and Outcomes Framework (QOF), aggregated at the MSOA level (GLA, 2023). This dataset combines GP-level data with the 2019 population estimates from the Office for National Statistics to estimate the percentage and number of obese adults in each MSOA. Similarly, the childhood obesity dataset identifies MSOAs with the highest levels of overweight children in reception and Year 6, which are viewable as below interactively.

Data Profile: Access to Healthy Assets & Hazards (AHAH) Version 3

Component Variables

Variable	Description	Domain	Country	Source	Date
lsoa11	Lower Super Output Area code (2011)	NA	England & Wales	ONS	2011
lsoa11	Data Zones	NA	Scotland	gov.scot	2011
ah3gamb	Distance to nearest **Gambling Outlet** (minutes)	retail	All	LDC	2019
ah3ffood	Distance to nearest **Fast Food Outlet** (minutes)	retail	All	LDC	2019
ah3pubs	Distance to nearest **Pubs/Bars/Nightclub** (minutes)	retail	All	LDC	2019
~~ah3off~~	~~Distance to nearest **Off licence** (minutes)~~ [REMOVED]	~~retail~~	~~All~~	~~LDC~~	~~2019~~
ah3tob	Distance to nearest **Tobacconists/Vape Store** (minutes)	retail	All	LDC	2019
ah3gp	Distance to nearest **GP Practice** (minutes)	health	England & Wales	NHS England	February 2022
ah3gp	Distance to nearest **GP Practice** (minutes)	health	Scotland	NHS Scotland	January 2022
ah3hosp	Distance to nearest **Hospital** (minutes)	health	England & Wales	NHS England	February 2022
ah3hosp	Distance to nearest **Hospital** (minutes)	health	Scotland	NHS Scotland	December 2021
ah3dent	Distance to nearest **Dentist** (minutes)	health	England & Wales	NHS England	January 2022
ah3dent	Distance to nearest **Dentist** (minutes)	health	Scotland	NHS Scotland	June 2021
ah3phar	Distance to nearest **Pharmacy** (minutes)	health	England	NHS England	January 2022
ah3phar	Distance to nearest **Pharmacy** (minutes)	health	Scotland	NHS Scotland	October 2021
ah3phar	Distance to nearest **Pharmacy** (minutes)	health	Wales	NHS Wales	November 2021
ah3leis	Distance to nearest **Leisure Centre** (minutes)	health	All	LDC	2019
ah3blue	Distance to nearest **Blue space** (minutes)	green/bluespace	All	OpenStreetMap	2021
ah3gpas	NVDI value indicating **Passive Green Space**	green/bluespace	All	Sentinel Satellite	2021
ah3no2	Annual mean **Nitrogen Dioxide** (μgm^3)	air	All	DEFRA	2019
ah3pm10	Annual mean **Particulate Matter** (μgm^3)	air	All	DEFRA	2019
ah3so2	Annual mean **Sulphur Dioxide** (μgm^3)	air	All	DEFRA	2019

Figure 2: Detailed variables of CDRC dataset (Access the dataset at: https://data.cdrc.ac.uk/dataset/access-healthy-assets-hazards-ahah)

The data for mental health modelling is Small Area Mental Health Index (SAMHI), which is a composite annual indicator of population mental health at LSOA level from 2011 to 2019 (Daras and Barr, 2020). SAMHI combined multiple sources of mental health data, such as NHS-Mental health related hospital attendances, GP Patient Survey, and Prescribing Data, where a positive SAMHI indicates relatively severer mental health issues in the area, whilst a negative SAMHI indicates for fewer symptoms of residents' mental health issues. On top of it, 11 independent variables had been selected for modelling, include household income, employment, physical health, education, environment, air pollution, green area, the percentage of the population over 65 years old, the percentage of men, population density, and the percentage of the population aged 16-29, derived from the English indices of deprivation (IMD) in 2015 and 2019 (ONS, 2024), and the total population, population density at LSOA scale, greenspace coverage, air pollution concentration data from London Data Store.

3.2 Research Design and Methods

The research workflow design diagram is identical for obesity and mental health, hence they are running in parallel following the same workflow shown in Figure 3, taking obesity as example for illustration. Geographic boundary files and datasets upon merging adult and childhood obesity rates were used to map obesity patterns in London, followed by appropriate exploratory spatial data analysis, spatial patterns recognitions (i.e., Global Moran's I and Local Moran's I clustering), and varied influential factors investigation on obesity among adults and children, with step-by-step methods adoptions included in the lower half of Figure 3.3. The project employs spatial regression models, including SAR and SEM models, to identify the influential factors for whole city, but uses localised model Geographically Weight Regression (GWR) to find their varied influences among London areas.

Anselin et al. (2006)'s Global Moran's I and Local Moran's I indices were firstly calculated to examine the existence of spatial autocorrelations for health data, as well as the potential spatial clusters and outliners (Equation 1), so that to decide which regression models will be the optimal for this study.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + u \qquad (1)$$

Traditional regression model Ordinary Least Square (OLS) is going to be used for preliminary regression, as one of the most classical types of regression analysis (Yang et al., 2016), which predicts the output variable as a linear combination of the input variables; but with more recognition of the existence of spatial autocorrelation, spatial regression models are to be tested as well. For example, if taking the mental health measure SAMHI as dependent variable, then the model will be expressed as in Equation 2.

$$SAMHI = \beta_0 + \beta_1 \text{ income score} + \beta_2 \text{employment score} + \beta_3 \text{education score} + \beta_4 \text{ health score} + \beta_5 \text{environment score} + \beta_6 \text{concentration} + \beta_7 \text{canopy \_tree} + \beta_8 \text{65aged} + \beta_9 \text{male ratio} + \beta_{10} \text{ density} + \beta_{11} \text{16 29ratio} + u \qquad (2)$$

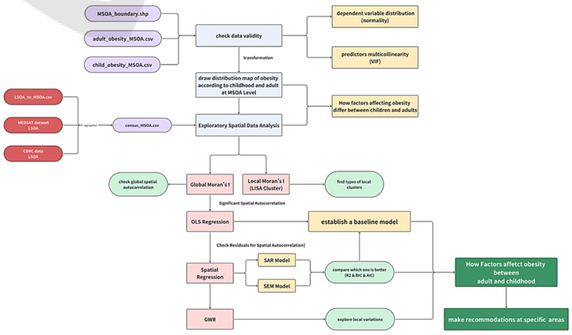

Figure 3: Research Design flowchart for Obesity (or Mental Health) Patterns in London

Spatial Lag Model (SLM) is deployed to account for spatial dependencies by incorporating a spatial lag of the dependent variable into the regression model, embracing the influence of neighbouring areas on the outcome of interest, and be expressed in Equation (3):

$$Y = \rho WY + X\beta + \epsilon \quad (3)$$

where Y is the dependent variable, ρ is the spatial autoregressive parameter, W is the spatial weights matrix, X represents the independent variables, β denotes the coefficients, and ϵ is the error term. By including ρWY.

Spatial Error Model (SEM) addresses spatial autocorrelation in the error terms rather than in the dependent variable. This model is suitable when the spatial dependence arises from unobserved factors that affect the error term, and can be formulated as in Equation (4):

$$Y = X\beta + \epsilon, \quad \epsilon = \lambda W\epsilon + \eta \quad (4)$$

where η is a normally distributed error term with mean zero and $W\epsilon$ represents the spatially lagged error term. Here, λ is the parameter that measures the degree of spatial autocorrelation in the errors. The SEM helps to correct for biases that might be introduced by spatial correlation in the error terms, leading to more accurate estimates of the relationships between the dependent variable and the independent variables.

Geographically Weighted Regression (GWR) as the last model, to capture local variations in the relationships between variables, offering a more detailed understanding of spatial dynamics. Unlike traditional regression models, which assume a uniform relationship across all locations, GWR calculates different regression coefficients for each area, addressing spatial differences in the data. The formula of the GWR model is displayed in Equation 5:

$$y_i = \beta_0 (u_i, v_i) + \beta_1(u_i, v_i)\, x_{1i} + \beta_2(u_i, v_i)\, x_{2i} + \; + \cdots \beta_k(u_i, v_i)\, x_{ki} + \epsilon_i \quad (5)$$

It detects spatial changes in relationships in the model and can reveal local features and trends in spatial data and handle spatial autocorrelation in data. Drill into the research design and methods for influential factor investigations, hierarchy of the selected factors are reflected in Figure 4, and similar for mental health measure (to replace the dependent variable from measure for obesity to measure for mental health), informed by empirical studies in Section 2.

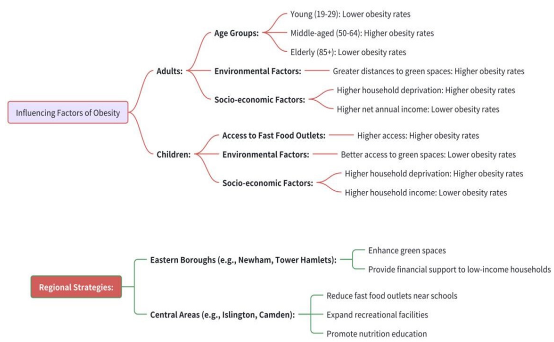

Figure 4: Variables for Modelling Obesity Patterns in London (similarly for Mental Health).

4 RESULTS

4.1 Spatial Patterns of Londoners Health

4.1.1 Physical Health – Obesity

Londoners' obesity patterns vary by age group in that, as reflected in Figure 5 on obesity rates among London regions, the redder in the map the higher values and vice versa. From left to right, maps are obesity patters for adults, children in Reception (ages 4-5), and children in Year 6 (ages 10-11) respectively.

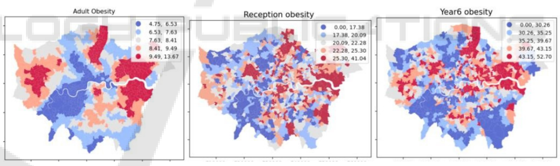

Figure 5: Londoners' Obesity Patterns by Group (Adult, Reception and Year 6).

It is apparent that, areas in the outer East (coloured in dark red) have higher obesity rates such as boroughs Barking and Dagenham and Havering. Besides, there were more adults with obesity in the western borough Hillingdon as well; whilst obesity rates among younger children in reception (aged 4-5 years old) were more dispersedly distributed, with areas in central London, such as Newham and Tower Hamlets, and outer areas such as Brent in the North; obesity among bigger children in Year 6 (ages 10-11) were also high in areas such as Barking and Dagenham, Tower Hamlets, and Hackney, but with wider distribution than the younger counterpart.

To identify the potential spatial autocorrelation, Global Moran's I had been calculated for each of the three age groups' obesity rates, in return with significant values as adult obesity at 0.6112, younger children at 0.2093 and older children at 0.2689. It is obvious that adults with obesity in London tend to cluster more in certain outskirt areas, whilst children with relatively much less pronounced clustering spatial pattern, but mostly in Northeast London. It implies that obesity issues among London adults may be more influenced by the neighbouring areas and local environment, hence leading to the localised spatial analysis visualised by LISA maps (Figure 6). In LISA maps, areas in red are HH clusters with high obesity rates and surrounded by similar neighbouring areas and predominantly located in the northeast parts of London regardless of age groups with consistently high obesity rates. On the contrary, areas in blue indicates LL clusters areas with low obesity rates surrounded by low obesity neighbours, indicating central and southwestern regions tend to be healthier physically. Meanwhile, areas with high obesity rates but neighboured by low obesity areas are colored in orange, whilst light blue areas are the opposite. Adults and bigger children also experience higher obesity in some western boroughs, whilst younger children have higher obesity in central-west London for limited area.

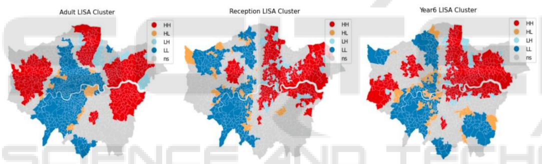

Figure 6: LISA clusters among adult, reception and year 6 (left to right).

4.1.2 Mental Health

Londoners' mental health indices distribution had been presented in Figure 7 for 2011 to 2019 respectively for comparison, but received similar spatial patterns. Redder areas with lower index values indicated better performance regarding residents' mental health, comparatively the bluer areas with positive mental health index values are those with worst performance of residents' mental health. From 2011 to 2019, residents' mental health has improved significantly with expanded redder areas.

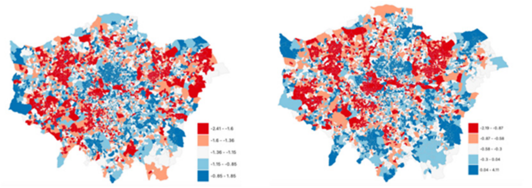

Figure 7 Mental Health Indices Patterns (left: 2011; right: 2019).

Upon calculating the global Moran's *I* measure, it was found that mental health index has significant spatial clustering patterns with a Moran's *I* value at 0.4875 in 2011 and 0.5341 in 2019. Localised LISA cluster mappings (Figure 8) further highlighted the clustering patterns with high-high (HH) areas indicating for those with worse mental health performance, and low-low (LL) areas with better mental health performance.

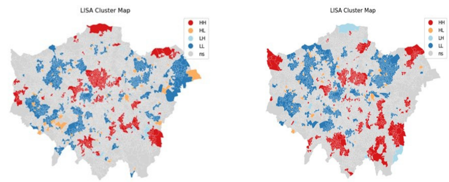

Figure 8 Mental Health Indices LISA maps (left: 2011; right: 2019).

Boroughs such as Islington, Camden and Hackney kept poorer mental health over time, while boroughs such as Enfield, Sutton and Lewisham improved in 2019 and no longer being hot spot clusters. On the other hand, boroughs such as Brent, Hounslow, Redbridge, Newham, Harrow and Wandsworth were better performed over time, but Havering became getting worse in 2019 from its good performance in 2011.

4.2 Influential Factors from Regression Modelling

4.2.1 Influential Factors for Physical Health

To better investigate the contributing factors for London residents' obesity, OLS, SLM and SEM regressions had been conducted with results summarised in Table 1.

Table 1: Regression Results for Obesity Modelling.

Variables	OLS		SLM		SEM	
	Adult	Bigger Children	Adult	Bigger Children	Adult	Bigger Children
Intercept	14.7687	33.5218	2.2114	958.0314	-----	1817.1489
Percent of Age 19～29	-0.0005		-0.0002		-0.0002	
Percent of Age 40～49	---		----		-----	
Percent of Age 50～64	0.001		0.0007		0.0006	
Percent of Age 85+	-0.0058		-0.0043		-0.0038	
Distance to nearest Fast food outlet	----	-47.1416	-----	38.4173	-0.0742	----
Distance to nearest Green Space	----	-1316.4992	0.8584	-656.2771	----	-879.9875
Net Annual Income	-0.0002	-0.0237	-0.0001	-0.0171	-0.0001	-0.0159
Percentage of unemployment	-3.3465	----	-----	-----	-----	953.2364
Percentage of household deprivation	------	47910	41.7626	40950.0536	40.5875	43658.535
Neighbourhood spillover			0.9857			
R-square	0.3346	0.3645	0.7662	0.5038	0.2356	0.3546

Comparing the 3 selected models, it is apparent that SLM is outperformed with R-square at 0.7662 for adults and 0.5038 for bigger children, indicating for the inclusion of neighbouring areas' influences (0.9857), especially for adults' obesity pattern. Income level exerted significant mediating effects onto obesity issue, regardless of age groups, but the influences were stronger to children than to adults. Percentage of residents at 40-49 years old is not related to regional adults' obesity level, but other age groups will be significantly related, especially the age group 50-59 years old, will drive mental health index higher. For children, community and family environment, such as the distance to the nearest fast-food outlet, the distance to the nearest green space, and the percentage of household deprivation had substantial effects on obesity rates, indicating that more convenient fast-food accessibility and more deprived families will drive children's obesity rate higher, while greenspace accessibility can mediate such obesity through easier exercise and outdoor activities.

4.2.2 Influential Factors for Mental Health

Similarly, London residents' mental health index and selected independent variables are modelled by OLS, SLM and SEM regressions for data in 2011 and in 2019 comparatively, with results summarised in Table 2.

Table 2: Regression Results for Mental Health Modelling.

	OLS		SLM		SEM	
	2011	**2019**	**2011**	**2019**	**2011**	**2019**
R Squared	0.5983	0.5499	0.7238	0.7443	0.5390	0.5045
Income Score	-0.5020	-0.4295	-0.3528	-0.2147	-0.2098	-0.0605
Employment Score	0.8584	0.8837	0.6874	0.6272	0.5968	0.5301
Education Score	-0.1516	-0.1191	-0.1407	-0.1246	-0.0539	-0.0510
Health Score	0.5239	0.4034	0.3919	0.2683	0.5391	0.3746
Environment Score	0.0989	-----	0.0501	-0.0306	0.0478	0.0115
Air Pollution Score	0.1139	-----	0.0675	0.0396	------	------
Canopry _Tree	0.0407	0.0302	-----	------	------	-------
65aged	0.2513	0.2931	0.2124	0.2356	0.1467	0.2326
Male Ratio	-0.1106	-0.1173	-0.0527	-0.0358	-----	--------
Density	-----	----	-0.0330	-----	-----	-0.0333
16-29ratio	-0.0607	0.0114	-0.0546	-----	-0.050	-0.0400
Spatial Weight	-----	----	0.5020	0.5924	0.7978	0.8145

It is obvious that SLM model still have the highest R squared value for both 2011 and 2019 data, hence should be the optimal model to be selected. Residents' mental health was mostly driven by their deprivations of employment and health, but can be mediated if be with a lower deprivation of income. Similarly, deprivation on education and the percentage of male residents could also help to alleviate local mental health issues. However, the neighbouring areas' mental health level is influential more and more greatly over time, as well as the percentage of aged populations (over 65). It also called our attention that at global scale, greenery didn't play significant influence onto Londoners' mental health, but air pollution concentrations are.

4.2.3 Localised Influences - GWR Model

To better understand the varied influences and model fitting among London boroughs, Geographically Weighted Regression (GWR) model had been applied to map out the factors' explanation ability for obesity and mental health measures. GWR allows for the examination of local variations in predictors, in Figure 9 it provides a deeper understanding of factors influencing obesity among London regions, by visualizing how well the model explains obesity rates across the study area.

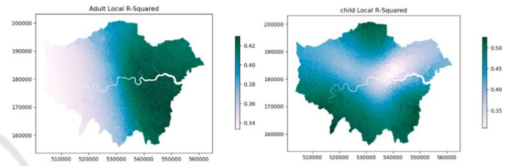

Figure 9: Local R-Squared map of GWR model among adults and children.

The local R-squared values for adults (left in Figure 9) are higher in East London especially the southeast such as Bromley, suggesting that the model explains obesity rates better in these regions. In contrast, the western areas show lower R-squared values, indicating that the model's explanatory power is weaker. For children (right in Figure 4.5), the local R-squared values are higher in the South and some northern areas, implying that the model performs better in explaining childhood obesity rates in these regions, but is weaker in explaining young people's obesity in central, and central east London areas.

It can also exhibit the varied influences onto dependant variable among London regions for each identified factor. For example, in Figure 10 presented the deprivation of income in London exerted varied influences onto mental health levels in 2011 and 2019, where outskirt areas were more driven by such economic inequality; on the other hand, it tends to cluster towards certain areas such as in Bromley over time.

Another factor, deprivation on employment has been investigated as well (Figure 11) in finding its expanded influences in the South and West London from 2011 to 2019, where central London and South London such as Croydon were always the most-hit areas for employment inequality driven mental health issues.

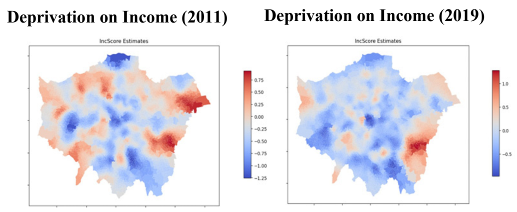

Figure 10: Local Influences on Mental Health from Deprivation of Income (left: 2011; right: 2019).

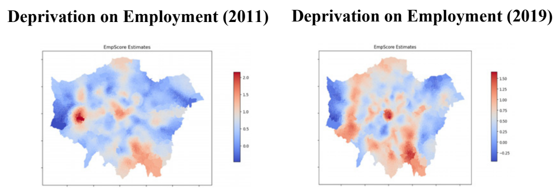

Figure 11: Local Influences on Mental Health from Deprivation of Employment (left: 2011; right: 2019).

In all, each factor can be mapped across London areas on their varied influences onto local mental health levels, either be driving forces or mediating effects. From a global perspective, greenery is not significantly influencing mental health, but it became influential locally in certain boroughs such as Hounslow. Income, education, employment, physical health, environment, greening, air pollution concentration, population density, and the percentage of young and elderly populations are important factors affecting mental health. These findings are conducive to designing localised intervention measures according to the featured circumstances of varied boroughs.

5 CONCLUSIONS

Obesity is a significant public physical health issue, leading to health risks, including developing chronic conditions such as heart disease, type 2 diabetes, and certain types of cancer. To understand and mitigate its potential impacts on Londoners' health could be meaningful to the society's development. The findings highlighted significant factors influencing obesity, differing between adults and children, underscoring the need for targeted, location-specific public health interventions. Specifically, for adults, age group compositions, green space access, household deprivation, and income were significant; while for children, access to fast food outlets, green space, household deprivation, and income levels were critical. Recommendations included promoting weight management programs at local community, improving green space access, and addressing socio-economic disparities. The GWR model highlights the significance of contextual and geographical factors in obesity. By focusing on local variations, more effective policies can be developed. For instance, in eastern boroughs like Newham and Tower Hamlets, strategies could include enhancing green spaces and providing financial support to low-income households. In central areas such as Islington and Camden, where childhood obesity is a major concern, interventions might include reducing fast food outlets near schools, expanding recreational facilities, and promoting nutrition education. Tailoring these strategies to regional needs can significantly improve public health outcomes and address obesity more effectively.

Mental health issue is not a sole challenge in London, instead serious mental illness (SMI) affected millions of people all over the world (James et al., 2018). In England, nearly three million adults were listed on local GP registers with depression in 2013-2014, and around half a million were diagnosed with a serious mental illness (SMI), which refers to people with schizophrenia, bipolar disorder or other psychotic illnesses (Grigoroglou et al., 2020). In London it is especially crucial to understand the mental health status over areas and time. The spatial patterns of London's mental health indices from 2011 to 2019 were largely consistent but varied at finer granularity for local distribution. Comparatively, the overall mental health indices in 2019 have improved significantly. Some boroughs, such as Islington, Camden and Hackey, kept poorer mental health performance from 2011 to 2019, whilst some other borough (Enfield, Sutton and Lewisham) exhibited great improvement over the time. On the contrary, outskirt boroughs such as Brent, Hounslow, Redbridge, Newham, Harrow and Wandsworth maintained good mental health performance over this period, but with exceptional deterioration in Havering from 2011 to 2019.

The spatial lag models (SLM) were found to be optimal in capturing maximum information hence explaining the dependant variables. The regional deprivations on income, employment, education, physical health, environment, air pollution, the proportion of the young and elderly population, population density, and the proportion of males significantly impacted mental health regardless of the year. Geographically, Hounslow, Redbridge and Harrow are boroughs consistently with good mental health, where Hounslow benefits from good employment equality, Redbridge and Harrow both benefit from better environmental equity, as well as better education in the latter. However, Havering stood out as an example for mental health deterioration due to severe income deprivation and air pollution pressures. Environmental factor greenery didn't exert a significant impact on London's mental health, but significantly affected mental health locally in specific boroughs. For example, Havering's mental health deteriorated significantly from 2011 to 2019 when driven by widened income gaps, high level of air pollution and less access to greeneries.

Mental health is affected by a mixture of multiple socioeconomic and environmental factors, future trajectory studies could be suggested to investigate the long-term impacts. Qualitative research can also be recommended to complement the findings interpretation from residents' point of view by interviews. The impact of each variable on mental health varies significantly across regions and years, reflecting the spatial heterogeneity of different regions. For example, Greening can mediate the mental health in Hounslow, but deprivation of employment could drive mental health level up. On the other hand, some factors only were influential in the area for certain time, such as deprivation on income and education were only negatively related with mental health in 2011, but no longer being significantly influential in 2019. Such variations might be the results from local policy interventions hence being worthwhile to get evaluated.

The project successfully addresses several limitations from empirical studies in that, it fills the gaps by simultaneously analyzing both adults and childhood obesity, offering a more comprehensive understanding of obesity across different age groups; compared the trajectory changes of mental health spatial patterns from 2011 to 2019 over both space and time, and highlights the necessity of region-specific policies through various spatial regression methods, demonstrating the importance of considering local context in public health interventions for both physical and mental health. Future research could benefit from integrating socio economic and environmental factors influencing obesity and mental health, such as air quality, dietary habits, and physical activity levels. Expanding the study to include longitudinal data or qualitative research data could provide insights into causal relationships. Incorporating a spatial-temporal analysis would allow for examining how childhood obesity transitions into adult obesity, mental health had been influenced by neighbouring areas, and revealing long-term trends and patterns. This approach would involve tracking cohorts of individuals over time to observe how health related challenges develop. By linking multi-sourced data, researchers can identify critical periods and factors that influence the health trajectories, providing a deeper understanding of how society conditions affect long-term health outcomes for citizens.

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