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Housing and mental health inequality in post-COVID-19 London

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Abstract. This study explores how housing-related factors have affected mental health inequalities in various districts of London in the post-COVID-19 period. Using the data from 2021 to 2022, this study explored three dimensions of housing: internal housing conditions, economic insecurity, and social environmental deprivation, and examined their correlation with life satisfaction (an alternative indicator of mental health). Through descriptive statistics, correlation tests and multiple linear regression analysis, the study found that the overcrowding rate, housing affordability and multiple deprivation index (IMD) score were significantly negatively correlated with life satisfaction. In contrast, fuel scarcity and housing quality had no statistically significant impact. The final model explains half of the variance of life satisfaction (adjusted $R^2 \approx 0.50$), indicating that housing burden pressure, space deprivation and overcrowding remain key determinants of mental health. Although the hypothesis that all housing dimensions affect mental health inequality is not supported, the results indirectly reflect that the impact of housing on mental health is complex and diverse. This study highlights the importance of addressing structural housing inequality and improving affordable, healthy and socially inclusive living environments in post-pandemic urban policies.

Keywords: housing inequality, mental health, post-COVID-19 London

1. Introduction

Extended lockdowns of COVID-19 led to widespread social problems, such as stressful living conditions and prolonged isolation, which triggered the development of mental illnesses, deepened health inequalities, and enhanced people's attention on housing environment [1, 2]. Mental health inequality means that some social groups are more vulnerable to mental distress and disorders [3,4]. However, contemporary research on post-COVID-19 has largely focused on downstream factors of mental health inequality, such as healthcare, with little attention paid to upstream structural factors, such as housing, which play an important role in shaping mental health inequality [4, 5].

Housing-related factors can influence mental health across multiple dimensions [4]. Physical conditions are essential, such as housing quality and space. Issues like overcrowding and mould can not only compromise physical health but also contribute to psychological symptoms like fatigue or anxiety [6]. Economic insecurity is also a significant factor in housing, such as the affordability of housing and fuel poverty. Insecurity brought by low affordability and physical unhealth caused by fuel poverty often forms anxiety, which can lead to insecurity and the absence of well-being [4,6]. Lastly, socio-environmental factors, including neighbourhood deprivation, crime, and lack of public services, can further exacerbate mental health inequalities, though these aspects remain underexplored in current research [4,7].

Based on the background, the research aims to explore the extent to which housing factors contribute to mental health inequality across London boroughs in the post-COVID-19 context, so that the gap in upstream determinants of post-pandemic well-being can be addressed. It focuses on three dimensions of mental health inequalities: internal housing conditions, economic conditions and wider socio-spatial structures. To guide this investigation, the following hypotheses are proposed:

H_0 : There is no association between all housing dimensions (housing conditions, economic insecurity and social environment) and mental health inequalities across London boroughs.

H_1 : There is an association between all three housing dimensions and mental health inequalities across London boroughs.

2. Data and methods

Table 1. Variable selections and data sources

Dimension	Variable	Description	Type	Source
Mental Health	Life Satisfaction	Life satisfaction is from the personal well-being table. This table includes four indicators: life satisfaction, happiness, worthwhile and anxiety. The personal well-being scale ranges from 0 to 10, where 0 signifies an individual not experiencing the specific measure at all and 10 represents experiencing it to the highest level. In this study, life satisfaction was used to represent the degree of mental health inequality.	Dependent	Trust for London (2022) [8]
Housing Conditions	Overcrowding Rate (%)	% of household accommodation has sufficient space by borough	Independent	Greater London Authority (2021) [9]
Housing Conditions	Housing_Quality(%)	% of homes meeting at least 'Good' standard by borough (based on Care Quality Commission Rating)	Independent	Greater London Authority (2021) [9]
Economic Insecurity	Fuel_Poverty(%)	% of households in fuel poverty by borough	Independent	Department for Energy Security and Net Zero (2022) [10]
Economic Insecurity	Housing_Ability(%)	% of house prices to earnings by borough This is a key indicator of housing affordability in London boroughs. The ratio is calculated by dividing the average house price by the median income of a borough.	Independent	Office for National Statistics (2024) [11]
Socio-environmental factor	IMD_Score (Index of Multiple Deprivation average score)	IMD has been aggregated in seven dimensions to score the relative deprivation of local authorities in the UK. In this study, a borough-level 'average score' was used to reflect inequalities in mental health resulting from social environment at the district level.	Independent	Greater London Authority (2019) [12]
Labor &Income	Income_Equality	% of earning above the London minimum wage by borough	Control	Greater London Authority (2021) [9]
Labor &Income	Unemployment	% of unemployment per borough for 16-64 year olds in 2021	Control	Office for National Statistics (2024) [13]

The data sources of the study are in Table 1. Most data in this study were collected between 2021 and 2022 due to the post-pandemic research context. This period was the peak of the COVID-19 crisis with high housing stress and mental health [14]. Focusing on this point can capture the lasting impacts of the pandemic on housing and mental health inequalities. The analysis was conducted at the level of London borough, covering 33 boroughs (22 outer and 11 inner), ensuring spatial consistency and comparability across key variables [15].

2.1. Variable selection

This study selected variables across three dimensions to investigate the relationship between housing and mental health inequality. Internal housing conditions (overcrowding rate and housing quality), economic insecurity (housing affordability and fuel poverty), and social environment (Index of Multiple Deprivation (IMD). IMD reflected deprivation across seven dimensions (income, employment, health, education, housing and services, environment, and crime) [16], which allowed for more systematic assessments of disadvantaged social environments and their impact on mental health inequality. The dependent variable was life satisfaction, a widely used and stable proxy for mental health [17].

Finally, to prevent extraneous variables from distorting the relationship between housing and mental health inequalities [18], this study included two control variables, unemployment and income equality, because the unemployment and income may affect mental health through stress and economic insecurity [19, 20].

2.2. Method

This study used R and R Studio to conduct descriptive and statistical analysis and construct multiple regressions for correlation analysis through R packages, such as Simple Features, ggplot2, dplyr, and car [21-23]. Firstly, some missing values were deleted since the fewer missing values. Then, scatter plots [24]were used for descriptive analysis, illustrating the distribution and relationship of variables. Then, Pearson correlation coefficient and the clustered heatmap were used to assess the correlation between the five variables of the three housing dimensions and life satisfaction [24, 25]. Furthermore, multiple linear regression models were constructed of variables related to housing and life satisfaction, and Variance Inflation Factor (VIF) and residual diagnostics were used to assess the validity of the models [26]. At this step, by diagnosing the model, this study identified and removed outliers, and then introduced control variables to enhance the robustness of the multiple regression model Finally, spatial visualization [27] was used to compare life satisfaction with key predictors.

3. Results and analysis

3.1. Descriptive analysis

Firstly, this study used scatterplots to visualise the relationship between the three dimensions of the variables (housing conditions, economic insecurity, and socio-environmental factors) and life satisfaction using scatterplots [24].

For the housing conditions, based on Figures 1 and 2, the overcrowding rate and life satisfaction were negatively correlated, indicating that boroughs with more crowded housing tend to report lower subjective well-being. In contrast, no clear pattern was observed between housing quality and life satisfaction. The second dimension was economic security, categorised as housing affordability and fuel poverty. Figures 3 and 4 showed that housing affordability and life satisfaction were negatively correlated, suggesting that areas with less affordable housing tended to report lower well-being. Unexpectedly, fuel poverty and life satisfaction were slightly positively correlated, which contradicted existing literature findings and indicated the need for further investigation. The third dimension was the social environment. Figure 5 showed that the average IMD score and life satisfaction were negatively correlated, indicating that residents in more deprived boroughs reported lower levels of subjective well-being.

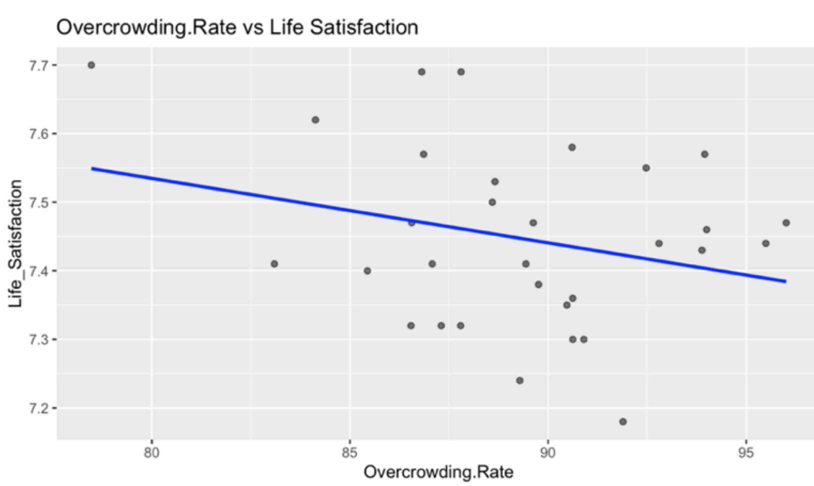

Figure 1. Correlation between overcrowding rate and life satisfaction

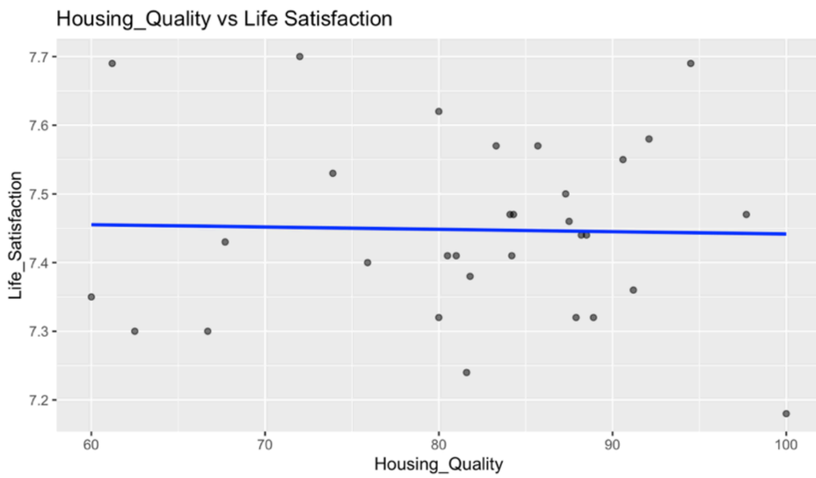

Figure 2. Correlation between housing quality and life satisfaction

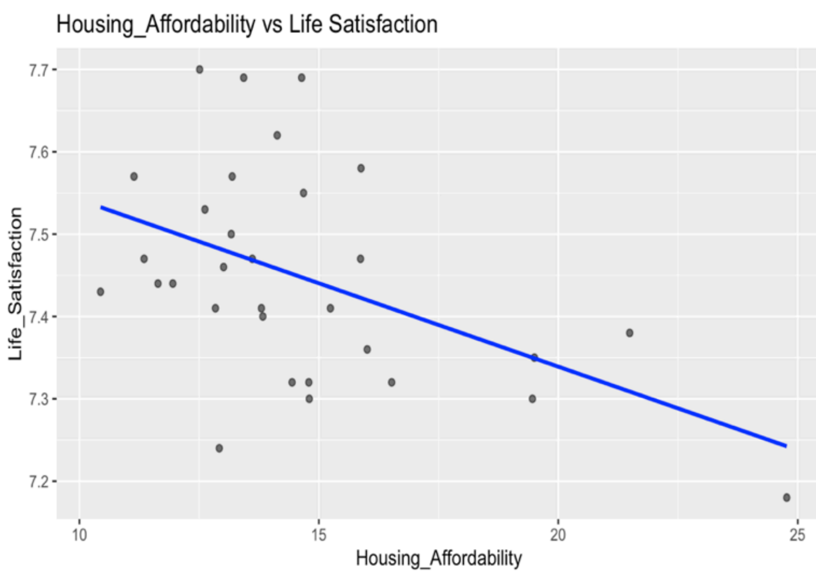

Figure 3. Correlation between housing affordability and life satisfaction

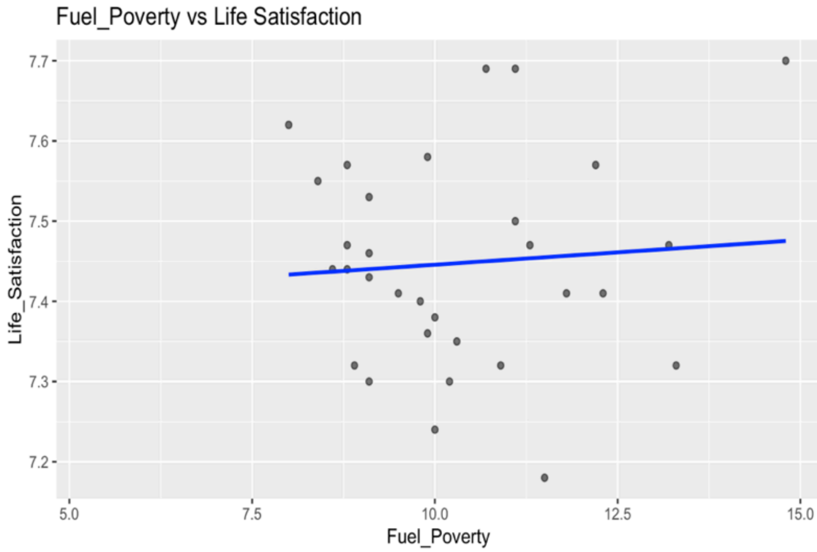

Figure 4. Correlation between fuel poverty and life satisfaction

Figure 5. Correlation between IMD score and life satisfaction

3.2. Correlation analysis

To quantify the strength and direction of these associations, Pearson correlation coefficients (r) were calculated (Table 2) [24]. Only housing affordability showed a statistically significant negative correlation with life satisfaction ($r = -0.479$, $p = 0.0064<0,01$), suggesting that affordability was the most influential economic factor in the dataset. Other variables, including overcrowding rates, fuel poverty, IMD scores, and housing quality, were not statistically significant (all $P>0.05$). A clustered heatmap (Figure 6) was also used to visualise intercorrelations between the independent variables (McKenna, 2016). A strong correlation was found between the overcrowding rate, fuel poverty ($r=-0.66$) and IMD score ($r=-0.71$), indicating potential multicollinearity in the regression model.

Table 2. Pearson correlation coefficient analysis between the three-dimensional variables and life satisfaction

Variable	Correlation	p_value	CI_lower	CI_upper
Housing_Quality	-0.027	0.8863	-0.378	0.331
Overcrowding.Rate	-0.270	0.1419	-0.570	0.093
Housing_Affordability	-0.479	0.0064	-0.712	-0.150
Fuel_Poverty	0.076	0.6830	-0.286	0.419
IMD_Score	-0.216	0.2438	-0.530	0.150

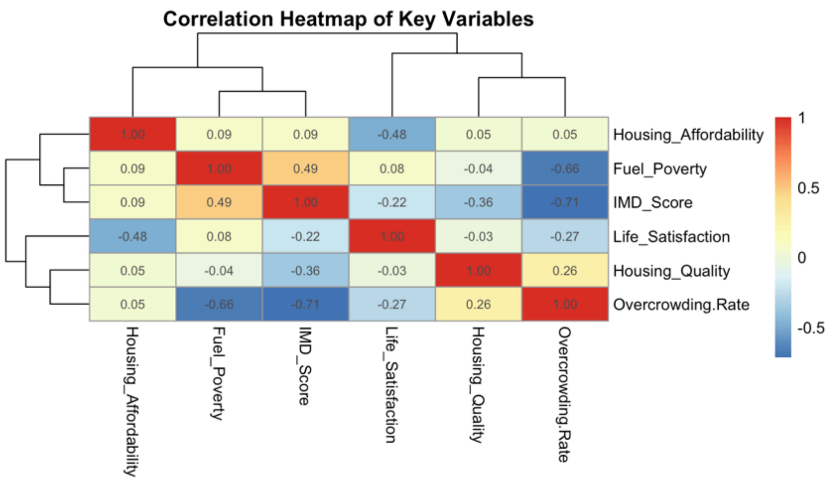

Figure 6. Housing variables clustered heatmaps

3.3. Multiple regression

Correlation analysis only reveals individual relationships, but multiple linear regression can evaluate the joint effects of all independent variables on life satisfaction while controlling for unemployment and income equality [28].

As shown in Table 3 and Table 4, the overall model was statistically significant ($p = 0.000749 < 0.01$), explaining approximately 46.3% of the variance in life satisfaction (adjusted $R^2 = 0.4626$). Looking at the three dimensions of the variable, housing conditions: overcrowding rate ($\beta = -0.0287$, $p = 0.0014<0.01$) was a significant negative predictor of life satisfaction. Specifically, $\beta = -0.0287$ indicated that a 1 percentage point increase in overcrowding was associated with a 0.0287 decrease in life satisfaction score. In contrast, housing quality ($p = 0.6274 > 0.05$) was not statistically significant, indicating that this predictor was not significantly related to life satisfaction. Economic Security: Housing affordability ($\beta = -0.0150$, $p = 0.0172<0.05$) showed a statistically significant negative correlation, whereas fuel poverty ($p = 0.6927 > 0.05$) was not statistically significant, indicating that this predictor was not significantly related to life satisfaction. Social environment: The IMD score ($\beta = -0.0174$, $p=0.0009 < 0.01$) was highly significant and negatively associated with life satisfaction.

In summary, only the overcrowding rate, housing affordability, and IMD score had significant effects on life satisfaction, while fuel poverty and housing quality were not significant. This means that the current model does not meet the assumption that all three factors are related to the level of mental health inequality. Therefore, the alternative hypothesis H_1 is not supported.

Table 3. The regression outcome I

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Significance
(Intercept)	10.7277792	0.8470478	12.665	2.24e-12	***
Overcrowding.Rate	-0.0286854	0.0080158	-3.579	0.001449	**
Housing_Quality	-0.0009131	0.0018580	-0.491	0.627394	
Fuel_Poverty	-0.0059371	0.0148505	-0.400	0.692704	
Housing_Affordability	-0.0149712	0.0058648	-2.553	0.017175	*
IMD_Score	-0.0172378	0.0045780	-3.765	0.000903	***

Table 4. The model summary I

Statistic	Value
Residual standard error	0.09614 (on 25 DF)
Observations deleted due to missingness	2
Multiple R-squared	0.5521
Adjusted R-squared	0.4626
F-statistic	6.164 (on 5 and 25 DF)
p-value	0.000749

3.4. Model diagnostics and refinement

To ensure robustness, diagnostic tests were performed. Multiple covariance and outlier problems need to be checked in multiple regression to ensure that the regression results are accurately determined [26]. According to Table 5, there is no significant multicollinearity problem in the model (VIF <5). Meanwhile, residual plots (Figure 7) showed that the assumptions of linearity and homoscedasticity were satisfied. However, two outliers (boroughs 12 and 20) were identified and removed to improve the model. After removing the outliers, the updated regression (Table 6 and 7) achieved an adjusted $R^2 = 0.505$ ($p = 0.002$). Overcrowding rate, housing affordability, and IMD score remained significant predictors of lower life satisfaction. It can also be reflected in figures 8, 9 and 10. Figure 8 showed that areas with low life satisfaction and high overcrowding rates were concentrated in inner London, suggesting that high-density housing harms mental health. Figure 9 showed that boroughs with poorer housing affordability (larger percentages) were associated with reduced life satisfaction. Figure 10 showed that boroughs with higher IMD scores (higher levels of deprivation) tended to have lower life satisfaction.

3.5. Summary of findings

The regression results indicate that overcrowding, housing affordability, and deprivation (IMD score) are robust predictors of life satisfaction. However, this study explores the common relationship between all three dimensions of housing conditions, economic insecurity, and social environment and mental health inequality, which means this study requires that the p-value of all factors be less than 0.05 to meet the hypothesis in this research. However, housing quality and fuel poverty still did not reflect a significant relationship with life satisfaction ($p > 0.05$). This means that the study is still unable to recognise the H_1 and refuse H_0 . Hence, statistically, there is no association between housing conditions, economic insecurity, social environment and mental health inequality.

This does not exactly match the findings of the literature, which consistently emphasise the strong influence of physical housing conditions, economic stability, and the social environment on mental health outcomes [4, 5, 7]. One possible reason is the scale of analysis [29], concentrating on data at the London borough level rather than the more granular ward level, which may mask inequalities within boroughs. Other limitations include the relatively small sample size (33 London boroughs), missing data points for some indicators, and confounding factors (such as educational level), which may have weakened the statistical and analytical power for the multi-dimensional variables. Finally, the analysis is based on a linear regression framework and cross-sectional analysis, which may not fully capture the potentially non-linear relationship between housing and mental health and infer causality [30, 31]. To enhance the credibility of the model, future studies should use more granular data (e.g., London Lower Super Output Area or ward level) and expand the range of indicators.

Table 5. VIF test

Variable	VIF
Overcrowding.Rate	2.957969
Housing_Quality	1.190828
Fuel_Poverty	1.893866
Housing_Affordability	1.072247
IMD_Score	2.277975

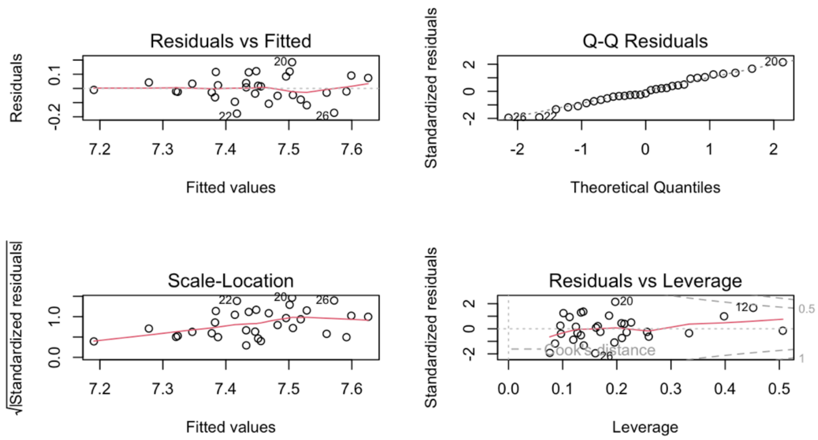

Figure 7. Regression diagnostics

Table 6. Regression outcome II

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Significance
(Intercept)	9.317509	0.965118	9.654	5.7e-09	***
Overcrowding.Rate	-0.023089	0.008565	-2.696	0.013910	*
Housing_Quality	0.001675	0.001903	0.880	0.389295	
Fuel_Poverty	0.018730	0.017665	1.060	0.301647	
Housing_Affordability	-0.017717	0.007083	-2.501	0.021170	*
IMD_Score	-0.016635	0.003992	-4.167	0.000476	***
Unemployment	-0.017877	0.011776	-1.518	0.144635	
Income_Equality	0.006845	0.005806	1.179	0.252278	

Table 7. The model summary II

Statistic	Value
Residual standard error	0.08069 on 20 degrees of freedom
Observations deleted due to missingness	3
Multiple R-squared	0.6333
Adjusted R-squared	0.505
F-statistic	4.935 on 7 and 20 DF
p-value	0.002269

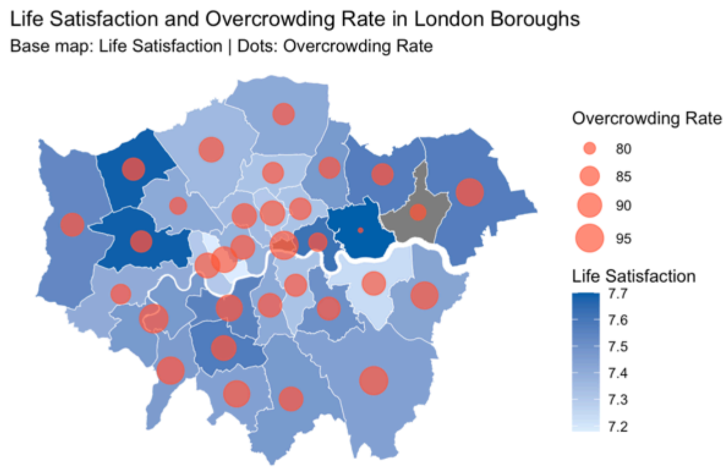

Figure 8. Life satisfaction and overcrowding rate

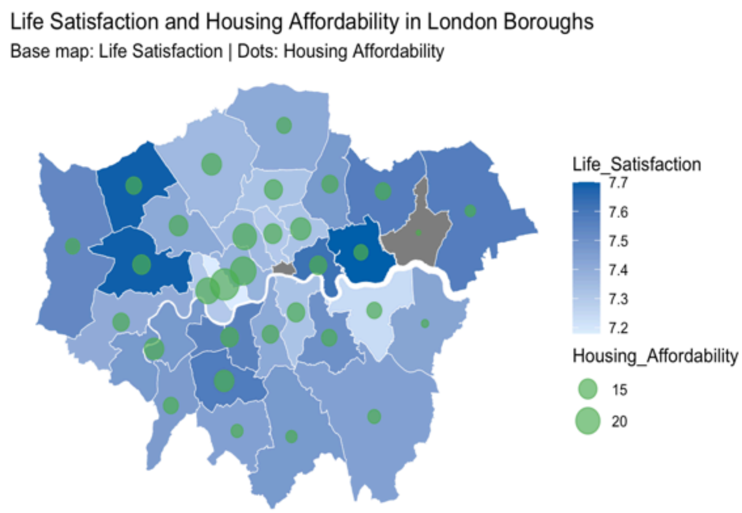

Figure 9. Life satisfaction and housing affordability

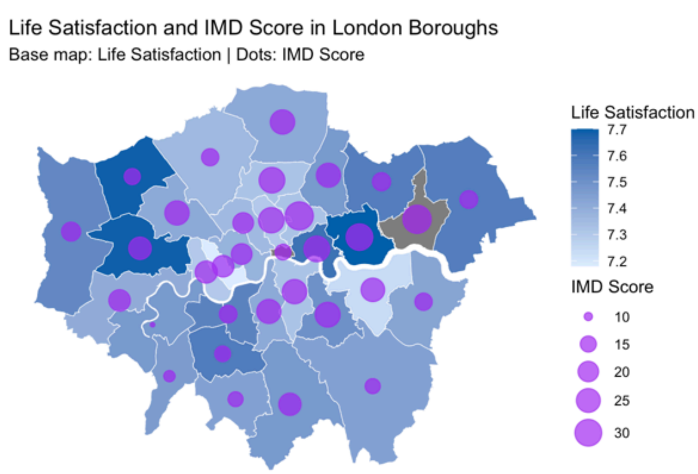

Figure 10. Life satisfaction and IMD score

4. Conclusion

This study investigated the relationship between housing-related factors and mental health inequality, as measured by life satisfaction across the post-COVID-19 context in London boroughs. Through a multidimensional framework, the analysis considered five key variables across three domains: internal housing conditions, economic insecurity, and socio-environmental disadvantage. The final regression model revealed that overcrowding, housing affordability and IMD scores were statistically significant and negatively associated with life satisfaction. By contrast, fuel poverty and housing quality were not significant predictors. Therefore, while the overall model explained approximately 50 % of the variation in life satisfaction, it did not support the hypothesis that all three housing dimensions significantly influence mental health inequality in this study.

This result is not entirely consistent with the literature's emphasis on the impact of material housing conditions, economic stability and social environment on mental health. From a data perspective, the reasons for this result lie in the small scale of the analyzed data, the scarcity of data samples, the absence of data, and the confusion of other factors. These possible factors have greatly weakened the model's statistical and analytical capabilities. In addition, from the perspective of the analysis model, the linear regression framework and cross-sectional analysis may not be able to fully capture the potential nonlinear relationship between housing and mental health and infer the causal relationship. Therefore, in the future, improvements can be made in terms of the quantity of data and the quality of the model to enhance accuracy.

Whilst the overall model does not prove the hypotheses of this study, the contribution of individual variables such as overcrowding rates, housing affordability and IMD scores to mental health inequalities still demonstrates that the dimensions of housing in influencing mental health inequalities are complex and multidimensional. These findings in the post-COVID-19 highlight the importance of addressing structural housing inequalities in the post-urban context since safe, affordable and dignified living conditions are more important than ever.

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