THE UNIVERSITY OF HONG KONG
FACULTY OF SOCIAL SCIENCES

The Impact of Social Vulnerability on Disease Transmission:

Mobility As a Mediating Factor

A capstone project report submitted in partial fulfillment for the degree of Master of Social Sciences in the field of Social Data Analytics (MSDA)

By

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Declaration

We declare that this capstone project report represents our group's own work, except where due acknowledgement is made, and that it has not been previously included in a thesis, dissertation or report submitted to this University or to any other institutions for a degree, diploma or other qualification.

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Abstract

COVID-19 has posed unprecedented challenges to public health systems worldwide, with numerous studies highlighting the roles of both population mobility and the social vulnerability in influencing the spread of the virus. However, few studies have examined how these factors interact, particularly whether social vulnerability may affect COVID-19 transmission indirectly through its impact on mobility. To address this gap, this study investigates the mediating role of mobility in the relationship between social vulnerability and COVID-19 transmission across Hong Kong's 18 districts. Using a mediation analysis framework with Geographically and Temporally Weighted Regression (GTWR) model embedded, we constructed a weighted Social Vulnerability Index (SVI) and assessed its association with both mobility and COVID-19 transmission rates. Our findings confirm that social vulnerability significantly influences COVID-19 transmission, with mobility serving as a key mediator in this relationship. Furthermore, the mediating effect exhibits marked spatial and temporal differences, providing a basis for targeted interventions in different regions and periods. These findings highlight the importance of considering mobility as a mediating variable in developing effective epidemic control strategies. This study emphasizes the need for localized and dynamic epidemic prevention measures tailored to the inequal social vulnerability characteristics and the evolving epidemic situation in each district, moving away from 'one-size-fits-all' approaches to enhance the scientific and sustainable nature of epidemic prevention efforts.

Contents

Chapter 1

Introduction

Since the outbreak of the epidemic in 2019, COVID-19 has continuously threatened global communities as a public health emergency. The emergence of 2021 Omicron variant and its sub-lineages posed new challenges to global health security and socioeconomic order, primarily due to their strong immune escape capabilities (Silva et al., 2022). Specifically, socially vulnerable groups exhibit weaker resilience, facing heightened health risks during crises (Huang et al., 2022; Karaye & Horney, 2020; Qiao & Huang, 2022). Moreover, human mobility has emerged as a critical determinant, accelerating viral spread (Baggio et al., 2021). The complex relationship between social vulnerability and mobility plays a critical role in influencing the spread of COVID-19 by intertwining various socioeconomic factors that exacerbate exposure risks.

Existing literature has highlighted the association between social vulnerability and COVID-19 in exploring pandemic transmission factors. Factors such as individuals' socioeconomic status, family structure, social identity, and living conditions lead to unequal capacities for epidemic risk response among different districts (Cutter et al., 2002; Mah et al., 2023). Generally, vulnerable groups hold more significant health and socioeconomic burdens, as well as increased infection risks (Atchison et al., 2021; Baena-Díez et al., 2020; Dowd et al., 2020; Huang et al., 2021). For instance, ethnic minorities are more exposed to community environments with severe pollution and crowded housing, exacerbating infection risks (Boserup et al., 2020; Cordes & Castro, 2020). Besides, COVID-19 mortality risk is highly concentrated at older ages due to reduced immunity and preexisting conditions (Dowd et al., 2020; Shi et al., 2020). Due to occupational characteristics of on-site work, vulnerable groups face higher exposure risks (Atchison et al., 2021; Bong et al., 2020). Additionally, low health insurance coverage and financial barriers to healthcare access further increase preventable COVID-19 mortality among them (Baena-Díez et al., 2020; Karaye & Horney, 2020).

As a critical determinant of COVID-19 transmission, human mobility's impact on transmission rates is central to tracking epidemic trends and evaluating the effectiveness of ongoing control measures. Given that the virus spreads via respiratory droplets, aerosols, and contact with contaminated surfaces, population mobility emerges as a key behavioral driver of the epidemic spread (Silva et al., 2022). Consequently, countries around the world widely implemented interventions such as social distancing, case isolation, and shielding to reduce human mobility, thereby lowering the effective reproduction number (R0) and limiting further transmission of COVID-19 (Nouvellet et al., 2021). Mobility patterns also have a direct impact on the spread of COVID-19, a research in Tehran demonstrated a significant relationship between public transit use and inter-city travel with the number of COVID-19 infections (Faraz et al., 2022). In the most affected US counties, there was a strong correlation between mobility patterns and COVID-19 growth rates (Gao et al., 2020). Several studies also have shown that restrictive measures on mobility reduce the risk of COVID-19 transmission in various cities(Cheshmehzangi et al., 2021; Ji et al., 2022; Schwarz et al., 2023).

Besides, many results of existing studies have indicated that there is a complex relationship between social vulnerability and mobility. Counties in the top quintile of the COVID-19 Pandemic Vulnerability Index (CPVI) had almost twice the rate of mobility-related COVID-19 transmission as counties in the lowest quintile (Huang et al., 2022). CPVI is developed by SoVI from the Centers for Disease Control and Prevention(CDC), which considers mobility and vulnerability factors (Chin et al., 2020). Luo revealed that state-level internal mobility restriction policies significantly weakened the positive impact of county-level economic vulnerability indices on COVID-19 infection rates, thereby indirectly curbing the spread of COVID-19. Moreover, the findings from a structural equation modeling technique indicate that socioeconomic deprivation, which is closely related to SVI, interacts with demographic factors and mobility patterns to create health inequalities in COVID-19 transmission (Luo et al., 2023). It is also reported that in wealthier areas, people have avoided more deaths during school closures and vaccinations (Ramírez & Lee, 2020). These studies indicate that mobility is a significant factor that interacts with social vulnerability during the virus transmission progress. However, the mechanisms by which mobility and social vulnerability interact to jointly influence the spread of COVID-19 remain unclear.

Based on the above literature review, we can summarize the following points: (1) SVI is significantly associated with COVID-19 transmission; (2) SVI is significantly associated with mobility; and (3) after controlling for mobility, the direct effect of SVI on transmission rates is weakened. Combining these with the mediation effect theory (Hayes, 2014), this study hypothesizes that SVI may indirectly affect the spread of COVID-19 through mobility, with mobility serving as the mediating variable. We aim to uncover the links among SVI, mobility, and

COVID-19 spread, underscoring the spatiotemporal differences in mobility's mediating role during the pandemic. By constructing an SVI framework for districts in Hong Kong and applying the Geographically and Temporally Weighted Regression (GTWR) model combined with mediation effect analysis, our study quantitatively assesses the mediating effect of mobility on the relationship between SVI and COVID-19 transmission, and further uncovers the spatiotemporal heterogeneity of this mediating relationship across different temporal and spatial scales.

The contributions of this study lie in the following aspects. In research methodology, this paper employs a novel transmission pathway framework incorporating mediating effects, systematically quantifying the direct impact of SVI on COVID-19 transmission and its indirect mechanisms through population mobility. Additionally, the study introduces the GTWR model to analyze the spatiotemporal dynamics of mediating effects, capturing their heterogeneity across different epidemic stages and regions, thus providing a new tool for dynamically tracking transmission mechanisms. As for policy level, the research offers empirical evidence for formulating targeted epidemic prevention strategies. Unlike previous 'one-size-fits-all' mobility reduction policies, we emphasize differentiated interventions based on the localized characteristics of each district, thereby enhancing the scientific basis and sustainability of epidemic control measures. Our findings can assist decision makers in improving their ability to respond to future public health emergencies, optimize resource allocation, and increase the efficiency of epidemic prevention and control.

Chapter 2

Data and Methodology

To examine and evaluate the mediating effect of mobility in the prediction of COVID-19 transmission by social vulnerability, we designed a mediation model based on GTWR model. This involves two parts: First, extracting dependent and explanatory variables from diverse datasets, including the latest COVID-19 data in Hong Kong, Hong Kong census data, Point of Interest (POI) data from Gaode Maps, and human mobility trend data from Google Mobility Reports (GMR). Then, regression analysis is conducted on the GTWR model, and performing mediation analysis based on this model, where the product of coefficients and Bootstrap are used to examine the mediating effect, along with analyzing the spatiotemporal characteristics of regression coefficients.

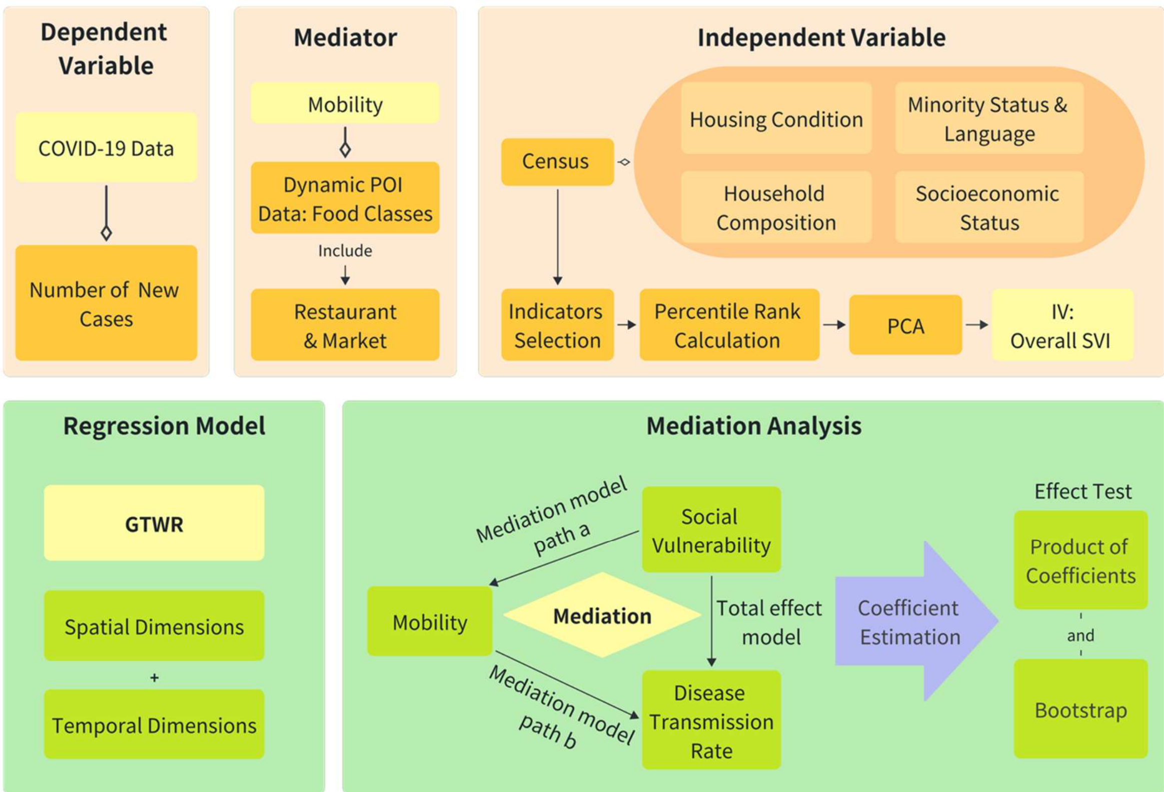

Figure 1 Research Framework

Figure 1 outlines our research framework. The study first defines key variables: using

COVID-19 new cases as the dependent variable, mobility (via restaurant and market dynamic POIs) as the mediator, and social vulnerability (derived from census data) as the independent variable. Then, it applies GTWR to analyze spatial-temporal variations and mediation analysis to reveal how social vulnerability influences disease transmission through mobility.

The dependent variable is the weekly number of new COVID-19 cases in Hong Kong from January 20 to March 20, 2022. The COVID-19 data is from the Centre for Health Protection, Department of Health, Hong Kong (chp.gov.hk). We collected 151,622 static POI data across 20 categories (e.g., market, restaurant, food beverages) from Gaode Maps. To construct dynamic POIs, we performed spatiotemporal fusion of the temporal population mobility data from the GMR with the visit change information of static POIs in each district (Qiao & Huang, 2023). Considering the average incubation period of COVID-19 and the time lag of the prediction model, we used the mobility trends from the seven days prior to the COVID-19 data release date as the estimation benchmark for dynamic POIs. By statistically analyzing the weekly visit frequency change of each static POI in GMR, we generated a spatiotemporally dynamic POI dataset. Through correlation analysis and industry classification, we ultimately focused on high-frequency essential food classes (including restaurants and markets) as the core research object.

2.1 SVI Construction

Social vulnerability refers to the socioeconomic and demographic factors that affect the resilience of communities (Flanagan et al., 2011). CDC identified and quantified these factors that describe a community's social vulnerability into a Social Vulnerability Index (SVI), which has been widely referred to by many researchers.

To construct the SVI, we used the latest census data in 2021 by Census and Statistics Department of the Hong Kong Government (census2021.gov.hk) and selected 8 socio-demographic variables covering four themes referring to CDC/ATSDR (2018), as shown in Table 1 to assess the social vulnerability value at the district level.

Table 1 Indicators of social vulnerability assessment

Theme	Indicator	Description	Influence
Socioeconomic status	Low education	Population over 15 years old with education below high school diploma (%)	+
	Income	Median monthly household income (HK$)	-
Household composition	Elderly	Population aged 65 and above (%)	+
	Single parent	Households with one parent (%)	+
Minority status and language	English speaker	Population whose usual language is English (%)	-
	Mainlander	Population born in mainland China/ Macao/Taiwan (%)	+
Housing condition	Housing size	Median floor area of housing (square meters)	-
	Housing public	Households living in public house (%)	+

The construction of SVI is usually based on socio-demographic variables, employing a ranking approach to eliminate dimensional effects, and equal-weighted aggregations to calculate the value. Considering the issue of varying importance among indicators, we employed principal component analysis (PCA) to assign weights to the indicators before aggregation (Huang et al., 2022; Qiao & Huang, 2022, 2023). Our construction is divided into three main steps: percentile ranking calculation, PCA weight calculation, and social vulnerability value calculation.

1) Percentile rank calculation.

$$P_{ij} = \frac{r_{ij} - 1}{N_j - 1} \tag{1}$$

Where P_{ij} is the percentile rank of each indicator j in district i, r_{ij} is the rank, and N_j is the total number of districts in research area. For indicators with a negative influence, the rank value was reversed. The larger the P-value, the greater the relative vulnerability, with the range from 0 to 1 representing an increase in vulnerability.

2) Defining weight by PCA.

We adopted the PCA to assign different weights to each indicator based on variance contribution. Although equal-weight aggregation is often employed in the traditional construction of SVI, sociodemographic indicators (such as income, educational level, age, etc.) make different impact on vulnerability in real life. Besides, PCA as a common linear dimensionality reduction method (Maćkiewicz & Ratajczak, 1993), transforms original indicators into uncorrelated principal components via linear combinations, thereby minimizing information redundancy and eliminating multicollinearity. Specifically, weights are derived from coefficients of the linear combination, which quantify each indicator's correlations and contributions to the variance explained by principal components. Thus, these coefficients serve as direct measures of indicators' importance.

Before the PCA, we employed the Kaiser-Meyer-Olkin (KMO) measure (Cureton & D'Agostino, 2013) and Bartlett's Test of Sphericity (Bartlett, 1951) to assess the suitability of the data for analysis. Specifically, the KMO evaluates the strength of partial correlation among indicators. If the partial correlation is low (the KMO value is close to 1, typically KMO ≥ 0.7), the data is suitable for factor analysis. Meanwhile, Bartlett's Test of Sphericity examines whether the covariance matrix is an identity matrix (i.e., whether the variables are independent of each other). If the null hypothesis is rejected ($p < 0.05$), it indicates that there are significant correlations among the indicators, making factor analysis appropriate.

We started with the centralized data matrix $X = [x_{ij}]_{n\times s}$ that represents the centralized original data, where s is the total number of indicators, and n is the number of districts. The PCA-derived matrix $P = [p_{ik}]_{n\times m}$ consists of m components, and $L = [l_{jk}]_{s\times m}$ represents the loadings of the original variables, which contribute to the respective principal components and are parallel to the eigenvectors. We also have $E = [e_k]_{1\times m}$ and $Ep = [ep_k]_{m\times 1}$ to represent the variance explained by each component in PCA. The weights were calculated using Equations (2)-(4):

$$coef' = \left[\frac{l_{jk}}{\sqrt{E}}\right]_{s\times m} \tag{2}$$

$$coef = \frac{coef' \times Ep}{\sum_{k=1}^{m} ep_k} = [coef_j]_{1\times s} \tag{3}$$

$$weight_j = \frac{coef_i}{\sum_{j=1}^{s} coef_j} \tag{4}$$

Here, $coef'$represents the score coefficient of each original variable to the PCA components, $coef$ is the comprehensive score coefficient that represents the overall contribution of each variable to the PCA components, $weight_j$ is the normalized weight of indicator j to the result of the PCA and the other variables are as previously stated.

3) SVI calculation

Once the percentile ranking and indicator weights were determined, we aggregated indicators across different themes to derive the thematic social vulnerability value for each district i denoted as SVI_{iz}, as well as the overall social vulnerability index SVI_i of district i.

$$SVI_{iz} = \sum_j P_{izj} \times weight_{zi} \tag{5}$$

$$SVI_i = \sum_z SVI_{iz} \tag{6}$$

2.2 GTWR Model

Due to the spatial heterogeneity caused by differences in social vulnerability across districts and the temporal instability resulting from changes in the epidemic transmission mechanism over time, we selected GTWR (Huang et al., 2010) as the core modeling method. This is because it can simultaneously characterize local features in both space and time, making it suitable for capturing this spatiotemporal heterogeneity. GTWR extends the traditional Geographically Weighted Regression (GWR) (Brunsdon et al., 1996) by incorporating the time dimension, allowing regression coefficients to vary across both space and time.

1) Model Formulation and Variable Definitions

The GTWR (Geographically and Temporally Weighted Regression) model introduces spatial coordinates and time variables into the regression process, enabling each observation point to have independent regression coefficients. The model can be formally expressed as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \tag{7}$$

Where y_i represents the dependent variable of the *i*-th observation point (in this study, it is the number of new cases in a certain district on a certain day), (u_i, v_i) denotes the spatial coordinates of the point, ti is the time point, x_{ik} is the *k*-th explanatory variable, the *k*-th regression coefficient $\beta_k(u_i, v_i, t_i)$ depends on the spatiotemporal position of the observation point and changes accordingly, and ε_i is the error term.

The core of the model is to construct a space-time weight matrix $W(u_i, v_i, t_i) = \text{diag}(w_{i1}, w_{i2}, \cdots, w_{in})$, which is used to measure the proximity of different observation points in the geographical space and time dimensions, and assign corresponding regression weights accordingly. The calculation form of the weight is as follows:

$$w_{ij} = \exp\left(-\frac{\left(d_{ij}^{ST}\right)^2}{b^2}\right) \tag{8}$$

In the above weight function, d_{ij}^{ST} represents the distance between observation points i and j in the standardized spatiotemporal coordinate system, that is, a comprehensive measure considering both geographical spatial distance and temporal distance. The calculation of the weight w_{ij} depends on the bandwidth parameter b, which controls the decay rate of the weight. The weight decays exponentially with the increase of distance, to ensure that the model is fitted in the local area and improve the stability of estimation.

More specifically, the GTWR model includes two bandwidth parameters simultaneously: the spatial bandwidth (denoted as bw) and the temporal bandwidth (denoted as τ). They respectively determine the relative weights and influence ranges of spatial distance and temporal distance in the overall weight calculation. After normalizing the spatiotemporal distance, these two bandwidths will jointly affect the value of d_{ij}^{ST}, and finally determine the magnitude of the weight w_{ij}. The spatial bandwidth 'bw' controls the model's sensitivity to information from neighboring areas. A smaller value makes the model more dependent on geographically adjacent points. A larger value assigns more weight to distant points. The temporal bandwidth τ determines the model's dependence on adjacent time observations. A smaller bandwidth makes the model more inclined to capture short-term changes in time. A larger bandwidth represents a smoother time effect.

2) Model Specification and Variable Processing

This study employs the Gaussian kernel function as the weight function, which features continuity, smoothness, and a single peak. It assigns higher weights to nearby neighbors and rapid decay to distant ones, making it suitable for describing the local influence structure in both space and time during the epidemic spread. Meanwhile, the optimal bandwidth parameters are selected through the cross-validation method to ensure the best model fitting results

Given the dense administrative divisions and small spatial scale in Hong Kong, this paper uses the fixed bandwidth approach for modeling to avoid the problem of sparse samples caused by over-localization.

In the specific modeling process, two variables, the overall social vulnerability index (overall SVI) and the mobility variable (related to restaurant and market), are selected as explanatory variables. The input matrix is constructed based on the selected variables, and all explanatory variables are standardized, meaning they are transformed into a standard normal form with zero mean and unit variance. This ensures that the contribution of each variable to the model is not affected by its original numerical scale.

As the number of daily new cases varies significantly across different time periods, and to reduce the influence of extreme values, the dependent variable undergoes a log transformation prior to modeling. This helps compress the data range and improves estimation stability.

3) Multicollinearity Detection

Since the underlying estimation logic of the GTWR model still relies on local OLS regression, if there is multicollinearity among explanatory variables, it may lead to unstable regression coefficients and expanded estimation biases, particularly in models involving repeated fitting across multiple spatiotemporal observation points. Therefore, to ensure the stability and interpretability of model parameters, it is necessary to conduct collinearity detection before modeling.

In this study, a Variance Inflation Factor (VIF) test was performed on all explanatory variables before modeling. The VIF values of all variables were far lower than the common threshold of 10, indicating that there is no serious risk of multicollinearity in the variable system, which can meet the requirements of model estimation.

2.3 Mediation Analysis

Mediation analysis is a statistical methodology employed to examine how one variable influences another through one or more mediating variables (Baron & Kenny, 1986; Hayes, 2014). In this study, mediation analysis is utilized to investigate how SVI indirectly affects the spread of COVID-19 through the type of mobility data.

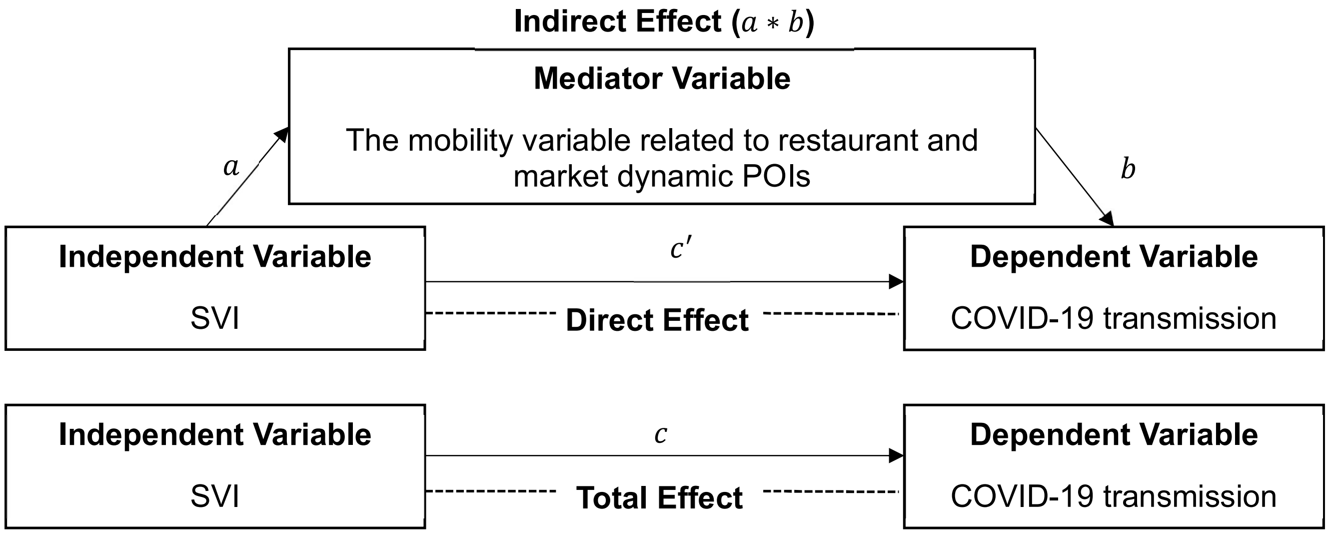

Figure 2 Basic Mediation Model

Considering the spatial heterogeneity and temporal dynamics of COVID-19 transmission, this study innovatively integrates mediation analysis with GTWR model to construct a spatiotemporal mediation effect model, Figure 2 presents a basic mediation model where the total effect is divided into direct and indirect (mediated) effects. Here are the individual components of the mediation model proposed in conjunction with the GTWR model:

(1) Total effect model (path c):

$$Y = cX + e \tag{9}$$

Equation (9) captures the overall impact of the independent variable SVI on the dependent variable (COVID-19 transmission) without considering the mediator variable (mobility variable).

(2) Model of the independent variable's effect on the mediating variable (path a):

$$M = aX + e \tag{10}$$

Equation (10) examines how the independent variable SVI influences the mediator variable (mobility variable).

(3) Direct effect model (path c'):

$$Y = c'X + bM + e \tag{11}$$

Equation (11) isolates the direct impact of the independent variable (COVID-19 transmission) on the dependent variable (SVI) after accounting for the mediator variable (mobility variable).

(4) Indirect effect (path $a * b$):

$$\text{Indirect Effect} = a * b \tag{12}$$

Equation (12) represents the effect transmitted through the mediator variable (mobility variable) from the independent variable (SVI) to the dependent variable (COVID-19 transmission).

(5) Total Effect Decomposition:

$$c = c' + (a * b) \tag{13}$$

The total effect is the sum of the direct effect and the indirect effect.

Also, given that mediation effect estimates $(a * b)$ typically don't follow a normal distribution, the nonparametric Bootstrap method is used to construct confidence intervals for the mediation effects (Preacher & Hayes, 2008). This involves drawing a sample with replacement from the original sample, calculating the mediation effect for this Bootstrap sample, repeating this process 1000 times, and then using the 2.5th and 97.5th percentiles of the resulting estimates to form a 95% confidence interval. A mediation effect is statistically significant ($p < 0.05$) if the 95% confidence interval doesn't include 0.

Chapter 3

Result

The previous section outlined data construction and methodology. This chapter presents our key findings and analyzes them in three parts: (1) SVI Construction Results; (2) Unraveling the Direct Effects of SVI and Mobility on COVID-19 Cases; (3) Mediation Analytics.

3.1 SVI Construction Results

This part presents the construction process and results of the SVI. First, Bartlett's and KMO tests were used to assess the suitability of data for factor analysis before PCA. Next, the weights of original indicators were derived by PCA to calculate the theme-based SVI indicators and an overall SVI. To explore the relationship between social vulnerability and epidemic transmission, Pearson coefficients were calculated and visualized via a heatmap.

Table 2 Statistics of PCA related tests

Feasibility test	P-value of Bartlett's Test of Sphericity	0.00
	KMO	0.65
Explained variance	Principal Component 1	5.81
	Principal Component 2	1.10
Explained variance ratio	Principal Component 1	68.8%
	Principal Component 2	13.0%
	Cumulation	81%

The P-value of Bartlett's Test of Sphericity was approaching 0.00, rejecting the null hypothesis that the correlation matrix is an identity matrix, which indicates a significant correlation among variables. The KMO value was 0.65, suggesting a moderate level of variable intercorrelation suitable for factor analysis. These results collectively support the applicability and validity of performing PCA on the dataset for further analysis. The cumulative proportion of variance explained by the first two principal components was 81%, which indicated that these two principal components jointly explained 81% of the total variance of the original data and retained the main information of the original data to a large extent.

Table 3 shows the weight distribution of each index under different topics, which is calculated based on the influence degree of the important principal components in PCA analysis on the original variables. Based on the weights of the indicators, we conducted an aggregation operation to obtain the comprehensive SVI, which is used to measure the overall level of social vulnerability in the district.

Table 3 Weights of indicators

Theme	Indicator	Weight
Socioeconomic status	Low education	0.106
	Income	0.116
Household composition	Elderly	0.174
	Single parent	0.115
Minority status and language	English speaker	0.070
	Mainlander	0.130
Housing condition	Housing size	0.164
	Housing public	0.124

To further explore the relationship between social vulnerability and epidemic transmission, we calculated Pearson correlation coefficients between the two variables and plotted a heatmap to visualize the correlation between social vulnerability indicators and the weekly number of COVID-19 confirmed cases. On the vertical axis (SVI variables), various social vulnerability indicators are listed (respectively, the overall SVI, socioeconomic status, household composition, minority status and language, housing condition), while the horizontal axis displays the weekly number of COVID-19 confirmed cases.

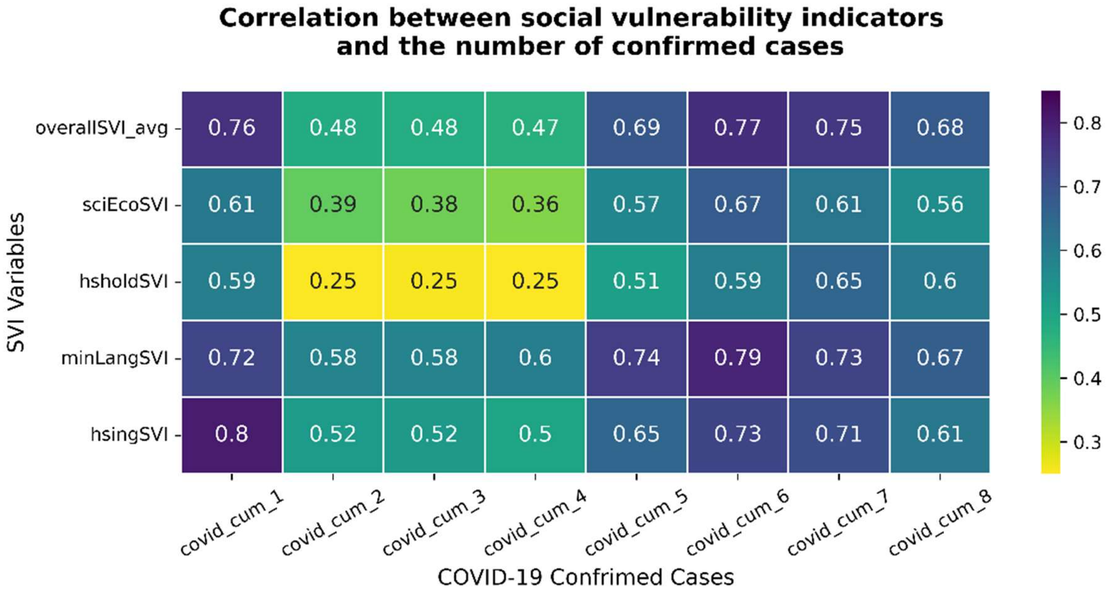

Figure 3 Correlations of social vulnerability indicators with the COVID-19 cases

The overall social vulnerability indicator maintains a relatively high correlation with the number of confirmed cases throughout the pandemic, with coefficients ranging from 0.68 to 0.77. In contrast, other SVI variables such as indicators of 'socioeconomic status' and 'housing condition' exhibit lower correlations with the confirmed cases in some periods. Based on these findings, we selected only the overall SVI indicator for the subsequent analysis. This choice was made to more effectively capture the association between social vulnerability and the spread of COVID-19.

3.2 Unraveling the Direct Effects of SVI and Mobility on COVID-19 Cases

This part assesses the direct effects of SVI and mobility on epidemic spread through the overall model regression, capturing the total effects of independent and mediating variables. By including both SVI and the mobility variable as explanatory variables in a full GTWR model, it allows for a direct estimation of their independent effects on disease transmission. This serves as a comparative foundation for the causal chain deconstruction in the subsequent mediation model, which separates the indirect path from SVI to COVID-19 transmission through mobility. By comparing the full model and the mediation model, we can verify whether introducing the mediator weakens or eliminates the direct effect, thereby confirming the presence and strength of the mediation mechanism.

1) Overall Model Performance

We construct a regional epidemic transmission mechanism based on the GTWR (Geographically and Temporally Weighted Regression) model, selecting the Gaussian kernel function and adopting a fixed bandwidth setting. After selecting the optimal bandwidth through cross-validation, the spatial bandwidth parameter bw=0.2 and the temporal bandwidth parameter τ=1.7 were finally set. The spatial bandwidth determines the geographic range of influence for local estimation, while the temporal bandwidth controls how far in time nearby observations affect the regression. In this study, the spatial and temporal bandwidths are interpreted in meters and days, respectively. The overall goodness of fit of the model is excellent, with an R^2 value of 0.941. The adjusted R^2, which accounts for model complexity to avoid spurious fitting caused by an excessive number of variables, is 0.927. The AICc value is 72.16, indicating that GTWR can effectively characterize the spatiotemporal heterogeneous impacts of explanatory variables on epidemic transmission.

In terms of local goodness of fit, the local R^2 values of each observation point are concentrated between 0.995–1.000, and the fitting effect remains highly stable across the spatial scale. As shown in Figure 4, almost all regions can well explain the epidemic changes at the local scale.

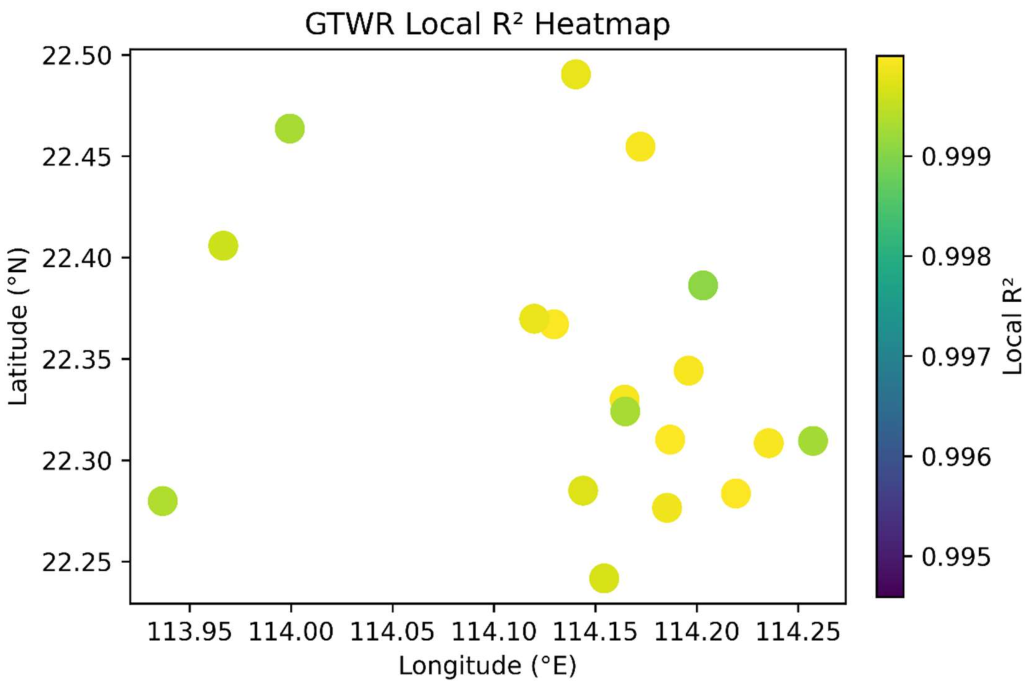

Figure 4 GTWR Local R² Heatmap

Additionally, evaluating the model's generalization ability from the perspective of prediction fitting, as shown in Figure 5, the GTWR model demonstrates highly consistent fitting effects on both the training set and the validation set. The R^2 values are 0.9410 (fitting) and 0.9269 (validation), respectively. The MAE and RMSE exhibit stability, and the error distribution is close to the 1:1 line, indicating that the model does not show obvious overfitting or underfitting.

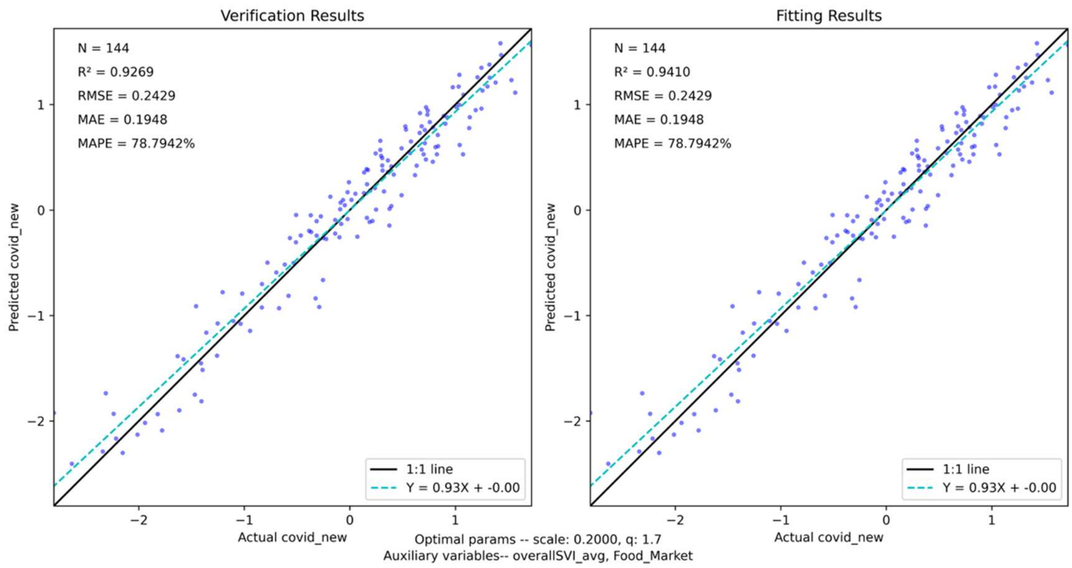

Figure 5 Verification Results & Fitting Results

Finally, to verify the rationality of the bandwidth settings in the physical space, this paper substitutes the selected optimal bandwidth parameters bw=0.2 and τ=1.7 into the standardized inverse deduction process, resulting in a spatial bandwidth of approximately 1656.8 meters and a temporal bandwidth of approximately 27.3 days. These values are consistent with the average spatial scale among Hong Kong's eighteen administrative districts and the temporal scale of epidemic spread, further indicating that the selected bandwidth parameters not only perform well in model fitting but also have explanatory power in actual spatial and temporal scales.

In the GTWR model, the regression coefficients of each explanatory variable show significant differences across different spatial and temporal points, reflecting the model's ability to capture spatiotemporal non-stationarity. The following figures display the coefficient variation trends of two key variables—the overall social vulnerability index (overall SVI) and mobility variable (dynamic POIs related to restaurant and market) —across different weeks and districts (see Figures

6 and 7).

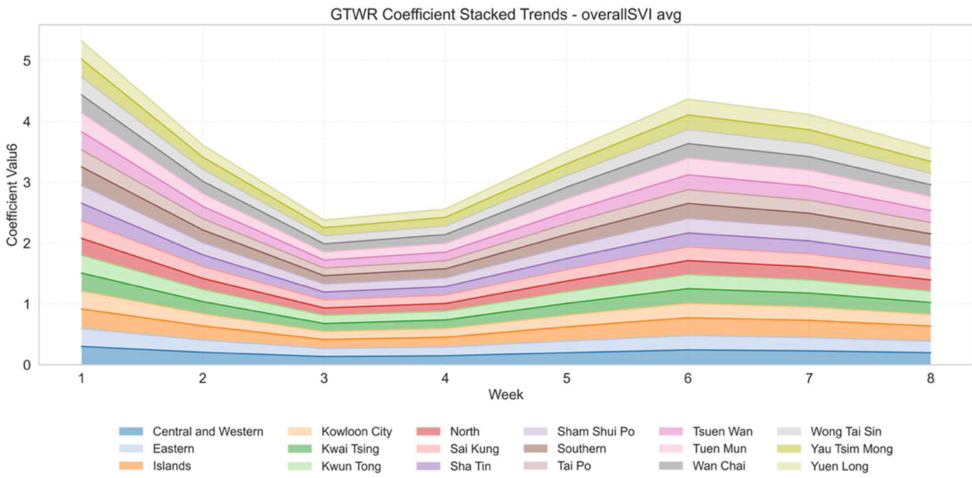

Figure 6 GTWR Coefficient stacked trends – overallSVI avg

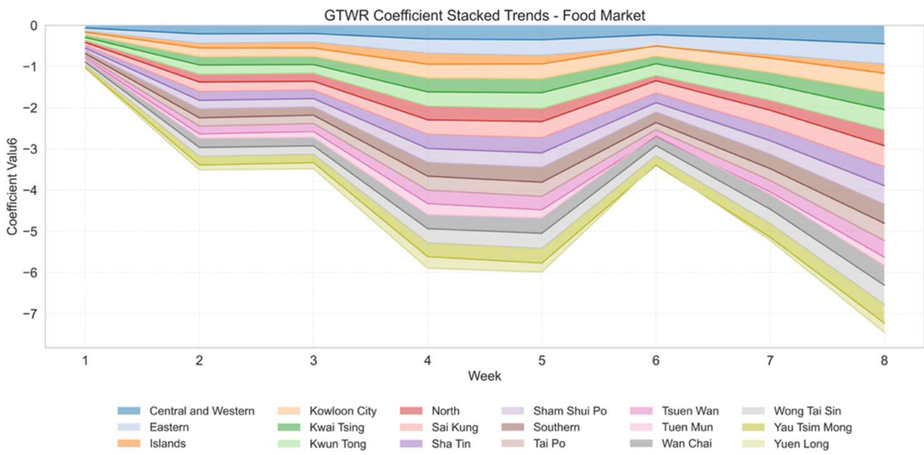

Figure 7 GTWR Coefficient stacked trends –Food Market (restaurant and market)

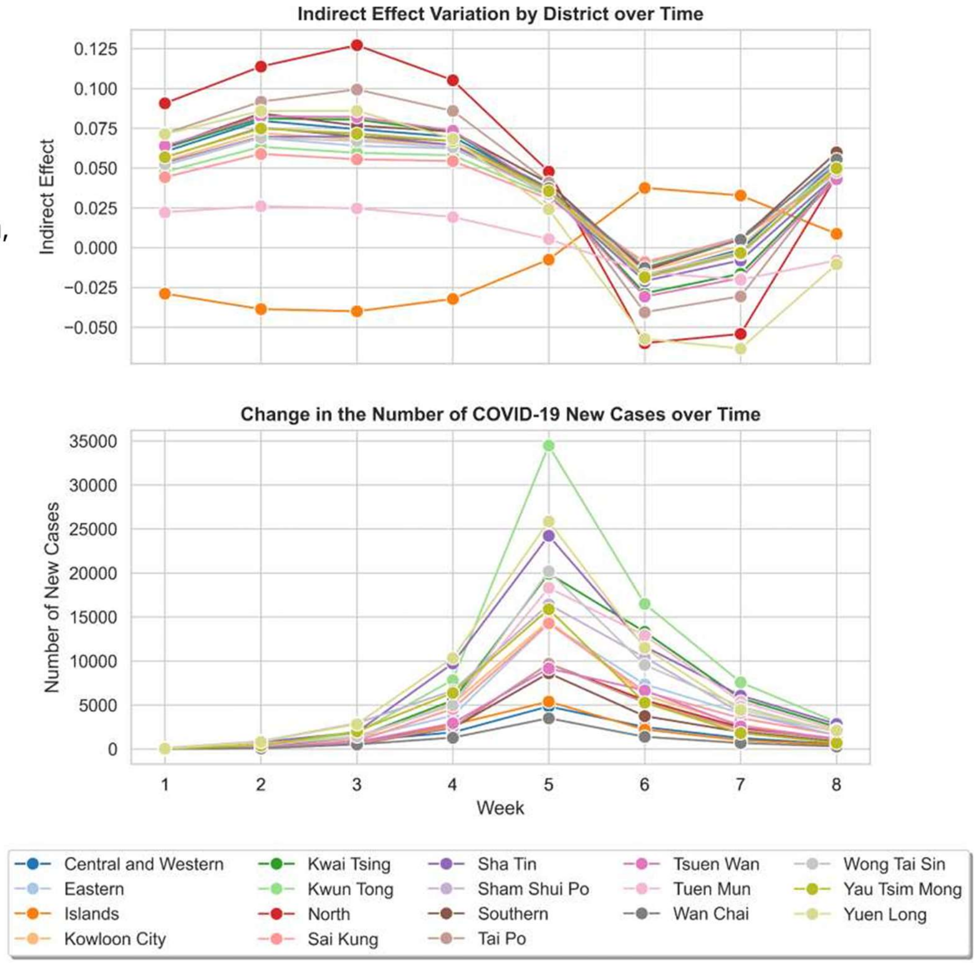

Figure 8 Indirect effects of COVID-19 and changes in the number of newly diagnosed cases

When considering the comprehensive social vulnerability index as an illustrative case, the regression coefficients consistently maintained positive values throughout all geographical areas examined. This persistent pattern demonstrates that localities exhibiting elevated vulnerability levels face proportionally more epidemic outbreaks (Figure 7). Meanwhile, measurable increases in the coefficient became statistically evident during the initial week of observation as well as the fifth and the sixth week periods. These distinct temporal fluctuations reflect an augmented capacity of the vulnerability metric to explain variations in daily new case counts across two critical epidemiological phases: the primary emergence stage of disease proliferation and an intermediate phase characterized by resurgent case growth. (as Figure 8 for COVID-19 case trends)

The regression coefficients corresponding to the restaurant and markets density variable were primarily characterized by negative values across the majority of study areas. While the overall trend suggests that higher concentrations of restaurant and markets are associated with lower infection rates, the GTWR model identifies spatial heterogeneity among districts. For instance, some areas such as Central and Western, Eastern, and Kowloon deviate from this general pattern. Rather than contradicting the overall negative association, these localized differences highlight the value of GTWR in capturing spatially varying relationships across regions. This observed inverse relationship potentially stems from several interacting mechanisms: adaptive collective behaviors within communities, more rigorous enforcement and limits within local markets, or potentially enhanced effectiveness of information dissemination. With regard to the time trend, the coefficients rebound after week 6, returning to near zero levels in some regions, and even showing weakly positive values.

These temporal changes and regional differences indicate that the magnitude and direction of influence exerted by distinct pandemic drivers exhibit considerable variation when measured across different epidemic phases and geographical settings. This evidence fundamentally underscores the continuously evolving character of outbreak transmission dynamics and its intrinsic spatial-temporal heterogeneity. These findings offer a comprehensive view of the direct impacts of social vulnerability and mobility, and serve as a critical baseline for the subsequent mediation analysis. By comparing the results of this full model with the decomposed indirect paths, we can evaluate the existence and strength of mobility's mediating role in the transmission mechanism.

3.3 Mediation analytics

The GTWR model results show a strong relationship between SVI and COVID-19 cases (R^2= 0.92; adjusted R^2 = 0.91) via basic regression. Further analysis confirms significant relationships between SVI and the mobility variable related to restaurant and market dynamic POIs (R^2 = 0.62; adjusted R^2 = 0.56), and between the mobility variable and COVID-19 transmission (R^2 = 0.89; adjusted R^2 = 0.87).

The a path (SVI to mobility variable) has an R^2 of 0.91 (adjusted R^2 = 0.89), and the b path (mobility variable to COVID-19 transmission) has an R^2 of 0.89 (adjusted R^2 = 0.87). The total effect (c path) shows a strong positive relationship (R^2 = 0.92; adjusted R^2 = 0.90). When controlling for the mobility variable, the direct effect (c' path) remains significant and improved the interpretability of the model (R^2 = 0.93; adjusted R^2 = 0.91), confirming the partial mediating role of mobility variable.

Table 4 Performance of mediation model in temporally enhanced schemes

	Coefficient/Effect (Mean)	R^2	Adjusted R^2	AICc
a Path (SVI → Mediator)	-0.08	0.91	0.89	114.97
b Path (Mediator → COVID-19)	-0.44	0.89	0.87	136.50
Direct effect (c' Path: SVI (M) →COVID-19)	0.18	0.92	0.90	107.23
Total effect (c Path: SVI →COVID-19)	0.22	0.93	0.91	83.14

Since the 95% confidence interval from the Bootstrap test is [0.03,0.04], which does not include 0, also indicates a statistically significant indirect effect of the SVI on COVID-19 transmission via human mobility related to restaurant and market.

As shown in Figure 8, the GTWR-based analysis indicates that SVI has a significant indirect effect on COVID-19 cases via mobility variable, with marked spatial and temporal differences. From week 1 to week 2, inter-district commuting was frequent and population mobility was unrestricted, allowing the virus to spread widely through public spaces. During this period, the indirect effect was pronounced in most districts, highlighting the significant role of the indirect transmission mechanism. Although the total number of cases remained low, an upward trend had already begun to emerge.

Starting from week 3, the number of cases increased rapidly across all districts, especially in Kwun Tong, where new cases exceeded 30,000 in week 5. The surge in cases led to the saturation of transmission chains and the diversification of transmission routes. Under such circumstances, controlling mobility alone is insufficient to effectively reduce the transmission of COVID-19, as the saturation of transmission chains and the diversification of transmission routes diminish the dominant role of mobility control measures. As a result, the indirect effect in most districts quickly dropped to near 0 by week 5.

From week 6 to week 7, as control measures were implemented, population mobility was significantly restricted, and the role of public spaces in transmission was effectively curbed. The indirect effect in each district remained close to 0, and the number of cases dropped rapidly, indicating effective epidemic control. The simultaneous decline in indirect effects and case numbers reflects the effectiveness of control measures targeting mobility restrictions.

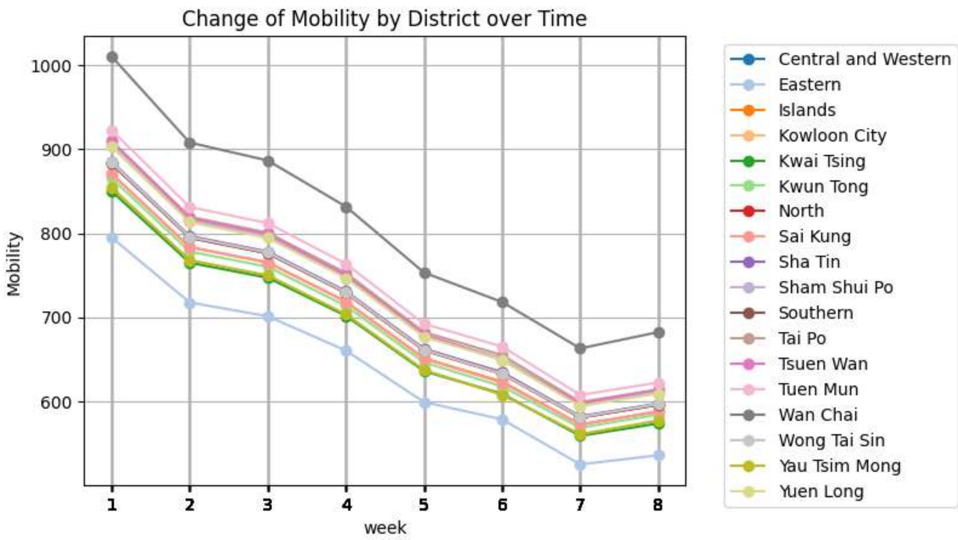

Figure 9 Change of mobility by district over time

By week 8, the indirect effect in all regions except the Islands rebounded slightly but remained far below earlier peaks. The number of new cases stayed at a low level, with only minor fluctuations. Although the local risk of indirect transmission increased, it did not lead to a significant rise in case numbers.

The indirect effect in Islands showed unique patterns during different stages of the pandemic. In the early stage, it was negative and lower than in other regions, showing that the virus transmission chains had not been established yet. When the indirect effect in urban areas started to decline, Islands saw a rise against the general trend, reaching a peak in week 6. However, the number of cases dropped similarly to other regions, without a major outbreak. Overall, the timing of the indirect effect peak in Islands did not match that of other regions, and it had bigger swings than usual. The opposite trend of indirect effects in the Islands District compared to other regions may be attributed to a combination of unique geographical isolation, population structure, and social behavior patterns. Geographical isolation could lead to a delayed establishment of virus transmission chains in the Islands District, resulting in a lagged change trend in indirect effects. Meanwhile, the social networks and activity patterns in the Islands District may have different impacts on virus transmission at various stages of the epidemic, causing the change trend of indirect effects to be inconsistent with other regions.

In summary, the peak of the indirect effect occurred before the peak in case numbers, indicating that the mechanism of indirect transmission holds significant predictive and early warning value in the initial phase of epidemic spread. The heterogeneity among regions further highlights the impact of spatial factors on the dynamics of COVID-19 transmission.

Chapter 4

Discussion

Understanding the complex association between social vulnerability, mobility and the dynamics of infectious disease transmission is essential for improving future outbreak prediction and prevention strategies. The discussion part will analyze the study in detail from four dimensions: summary of findings, highlights of the study, practical application value, and inherent limitations of the study.

4.1 Theoretical Contributions: Dual Pathways of Social Vulnerability on Epidemic Transmission

The results of the mediation analysis revealed two pathways through which social vulnerability affects the spread of the epidemic: First, social vulnerability has a direct impact on the number of cases—regions with higher social vulnerability are more likely to experience explosive growth in the number of cases due to factors such as a lack of medical resources and limited protective capabilities among residents. Second, social vulnerability indirectly increases the risk of transmission through human mobility. This mediating variable, mobility, is quantified within the confines of this investigation by the density associated with the distribution of restaurants and markets.

The formation of indirect effects may be related to the high-frequency travel needs of socially vulnerable groups and their tendency to choose low-end markets. Residents living in communities identified as having high social vulnerability, due to pressures stemming from economic hardship and the presence of other limiting factors, find themselves unable to accumulate significant stores of foodstuffs and necessary goods for daily living (Green et al., 2021). Furthermore, these areas are often underserved by delivery services, or residents may be unable to access such services due to economic limitations or cultural barriers. Consequently, they are compelled to make trips to markets to carry out purchasing activities much more often. Overcrowded housing conditions and densely populated communities further increase the likelihood of close interpersonal contact when residents go out. This pattern of behavior elevates the probability that these individuals will contract the virus. Within communities of this specific type, residents often depend to a greater extent on sources for daily supplies like small and medium-sized restaurants or markets. These typically include establishments such as open-air bazaars or local neighborhood vegetable stalls, rather than utilizing large supermarket chains. It is worth noting that such market premises often suffer from poor hygiene standards, overcrowding, and inadequate ventilation systems. These conditions collectively lead to a heightened risk linked to disease transmission.

4.2 Methodological Innovations: Spatiotemporal Heterogeneity Analysis of Mediating Effect of Mobility

Methodological innovation lies in employing GTWR to achieve the objective of revealing the mediating role of mobility and quantifying its spatial-temporal heterogeneous dynamics. While traditional approaches to mediation analysis assume that the effects are spatially and temporally homogeneous, this paper specifically utilizes GTWR to accurately depict the dynamic variation of the mediating effects in the dual dimensions of temporal change and spatial location. The model achieves this through a local regression approach.

The results show that the strength of the mediating effect of mobility is most significant at the beginning of the outbreak, but it shows a weakening trend subsequently. This weakening stems directly from the implementation of administrative measures aimed at explicitly restricting residents' travel. This temporal pattern implies that, specifically, mobility was one of the main factors of infection among highly socially vulnerable populations in the early stages of the outbreak. Conversely, following the enforcement of governmental restrictions targeting mobility, this factor ceased to operate as a core determinant influencing transmission outcomes. The strength of this mediating effect exhibited considerable variation in its intensity across different geographic regions. This geographic disparity is potentially attributable to the presence of disparities in local epidemic containment policies and measures enacted across different jurisdictions.

4.3 Practical Applications: Policy Implications Based on Social Vulnerability and Mobility

At the practical level, the findings of our study can assist governments in formulating epidemic prevention policies. During the initial weeks 1-2 phase of viral transmission, the indirect impact of mediator variable on epidemic spread reached its maximum intensity. Throughout this critical period, densely populated public spaces served as the dominant transmission channel in regions exhibiting high social vulnerability indices.

Governments should implement immediate crowd restriction measures while introducing targeted assistance programs for vulnerable populations. Such interventions should include organized delivery systems for distributing food and daily necessities to households, effectively reducing residents' necessity for frequent market visits. By household unit, limit the number of family members and the frequency of daily visits to markets for shopping. This can reduce crowding in public spaces while decreasing the exposure probability of vulnerable communities to the virus. Authorities should prioritize environmental remediation efforts or implement temporary closure protocols for markets operating in locations characterized by poor sanitation standards and inadequate ventilation systems.

Transitioning into the outbreak phase spanning weeks 3-5, the mediating effect of mobility substantially diminished, approaching negligible levels. This indicates that as the number of viruses surges, the proportion of infections resulting from close contact within households increases, while the relative impact of people visiting public spaces on virus transmission decreases. The indirect effects are no longer the primary route of virus transmission for vulnerable groups. At this stage, the effectiveness of mobility control measures will also significantly weaken. While policies continue to control the movement of people in public spaces, the focus should shift to addressing transmission pathways within communities and households. The government may implement measures to restrict family gatherings, setting a maximum number of participants per gathering and reducing mutual visits within communities.

Additionally, attention should be paid to the direct impact of social vulnerability on epidemic transmission, with particular emphasis on providing targeted support to vulnerable families with poor housing conditions, low economic status, or diverse ethnic backgrounds. Free distribution of protective supplies (such as masks and disinfectant) and basic medications to socially vulnerable groups should be provided to assist them in taking preventive measures within their household environments.

After entering the eighth week of the epidemic, the number of new cases gradually decreased and remained at a low level, prompting the government to relax its control measures. During this phase, the intermediary effect of mobility began to rebound, but the magnitude was lower than the previous peak. Therefore, it is still necessary to monitor mobility trends, though relatively relaxed control measures can be implemented. The rebound also reflects psychological issues stemming from prolonged isolation, resulting in a short-term surge in compensatory out-of-home mobility. In the future, when implementing control measures, governments should also consider residents' mental health and emotional well-being. Providing psychological counseling can help alleviate anxiety and thereby mitigate the rebound effect. For socially vulnerable groups, the government can implement a phased strategy to ease mobility restrictions: for example, in communities with a high proportion of elderly residents, non-single elderly individuals should remain prohibited from entering markets after the 8th week until new case numbers drop to a new low; simultaneously, markets or restaurants can reduce mobility intensity by shortening operating hours or only opening core areas.

4.4 Limitations and Shortcomings

There are limitations in the selection criteria for social vulnerability indicators. The measurement methods used in this study are inevitably limited by the available variables in the Hong Kong census dataset used, and may not include several established vulnerability indicators that are recognized in the epidemiological literature. Crucial omitted factors likely impacting vulnerability status encompass: health insurance coverage status across the population, household financial burdens represented by outstanding mortgage obligations, population segments identifying with disabilities, demographic variations in average household member counts, and communication barriers experienced by speakers of languages not widely used. The absence of these multidimensional indicators directly compromises the measurement accuracy of social vulnerability within our models. Consequently, the criteria applied to quantify vulnerability levels lack sufficient comprehensiveness, potentially reducing the analytical precision for identifying high-risk communities.

In defining the mediating variables, the analysis relies on a single operationalized indicator, the distribution density of restaurants, supermarkets, and markets. This measure captures only one specific dimension of population mobility, ignoring other key scenarios in which infection transmission often occurs. A number of high-risk public places associated with community mobility were not included in the assessment framework, with typical examples including major transportation hubs, healthcare facilities such as hospitals, and sports and leisure complexes. Residents of areas with high social vulnerability indices often need to travel to many different places due to their occupational status or basic needs. Therefore, relying on one category accessibility alone does not provide a complete picture of the overall exposure risk associated with mobility.

Moreover, the GTWR framework itself imposes two structural constraints that warrant careful consideration. First, the temporal dimension of our dataset is relatively coarse: eight weekly observations are modeled against 18 spatial units. When the number of time points is small, spatial weights tend to dominate the spatiotemporal kernel, and subtle coefficient changes over time can be blurred by strong spatial heterogeneity. Extending the observation window—or supplementing the weekly series with finer-grained daily data—would enhance the model's sensitivity to temporal variation and help disentangle time-specific effects from purely spatial ones. Second, the current analysis operates at the level of Hong Kong's 18 administrative districts. While this choice keeps model complexity manageable, it inevitably masks intra-district contrasts. Hong Kong contains pronounced socioeconomic gradients even within single districts—for example, between neighborhoods such as Central, Pok Fu Lam, and Yau Ma Tei. Employing a finer spatial scale, such as District-Council Constituency Areas or large street-block groups, would allow GTWR to capture micro-scale transmission dynamics and yield more nuanced policy insights.

Addressing these two methodological issues, increasing temporal depth and refining spatial granularity, which represents a clear agenda for future research and will substantially improve the robustness and practical relevance of GTWR-based epidemic modelling.

Chapter 5

Conclusion

The study systematically quantified the direct impact of social vulnerability on disease transmission and its indirect effects through mobility-mediated pathways. It also pioneered an in-depth exploration of the spatiotemporal heterogeneity of these mediating effects throughout the entire epidemic process by applying the GTWR method. Overall, these empirical findings provide operational scientific evidence for Hong Kong's health authorities, which is crucial for implementing forward-looking and timely intervention measures.

SVI is adopted as the independent variable, with mobility serving as the mediating variable and daily new COVID-19 confirmed cases as the dependent variable. SVI is significantly and negatively correlated with the resilience of the community to the impact of an epidemic. We constructed a multidimensional SVI and calculated the overall index value for each district to capture this complex concept. Mobility can be used as a key indicator to quantify the risk of viral infections in residents' out-of-home activities. For representing the mobility variable, we used the distribution density of restaurants, supermarkets, and markets. Daily new COVID-19 confirmed cases constituted the dependent variable, representing disease incidence.

We further constructed direct and indirect effect models to verify the mediating effect of mobility. To capture the complex spatiotemporal transmission dynamics, we employed GTWR models. The findings indicate that during the initial stage of the outbreak when the indirect effects of mobility peaked, early interventions should aim to reduce both the frequency and volume of visits to markets by socially vulnerable groups. In the subsequent weeks as the mediating effects weakened or diminished entirely, policy attention should shift toward addressing the direct effects of social vulnerability and intra-household transmission pathways. This may include limiting private gatherings and providing direct material support to vulnerable populations to mitigate further spread. In the later phase of the epidemic, although the growth in case numbers slowed, a notable rebound in indirect effects was observed. While this rebound did not reach previous peak levels, a phased relaxation of containment policies remains essential to prevent resurgence. Additionally, observed spatial heterogeneity underscores the necessity of tailoring interventions to the specific vulnerabilities present in different districts.

Future studies should improve GTWR models by adding time-dependent bandwidth adjustments and epidemiological time lags to better capture stage-specific mediation dynamics. Using panel Granger causality tests or time-varying panel vector autoregression models could also help clarify the two-way relationships between mobility and viral transmission while addressing endogeneity issues in mediation analysis.

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