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Original Article

Effect of Environmental Factors on the Spread of COVID-19 in the Neighborhoods of Qom Metropolis

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Abstract

Background & Aims: The prevalence of diseases such as COVID-19 has significantly impacted citizens' lives. Understanding the dynamics and triggering factors of disease on a small spatial scale leads to the formulation of strategies that ultimately result in disease control and reduction.

Materials and Methods: This applied, descriptive-analytical research utilizes spatial analysis and Geographic Information Systems (GIS) to examine the influence of environmental components on the prevalence of disease in the neighborhoods of the metropolitan area of Qom. The statistical population comprises individuals infected with COVID-19 from January 2020 to September 2021 (33,000 people) across 138 neighborhoods in Qom city. Hotspot analysis was employed to identify spatial patterns, and regression models were used to examine the impact of various indicators.

Results: The results revealed that the spatial pattern of disease in Qom neighborhoods was not uniform, with hotspots of disease prevalence located in affluent neighborhoods and hotspots of mortality found in less affluent areas. Additionally, 40% of COVID-19 prevalence was influenced by three indicators: the rate of students, the rate of individuals with over ten years of unemployment, and the mixed residential-commercial per capita in urban neighborhoods.

Conclusion: Based on the research findings, it has been determined that COVID-19 prevalence in the neighborhoods of Qom City was not uniform, with hotspots of disease in neighborhoods such as Amin Boulevarden, Saheli, Mosalla, Zeynabiyeh, and Jahān Bini, located in the southwestern part of Qom city. Furthermore, assessing the impact of social, economic, physical, and demographic indicators on COVID-19 prevalence in Qom neighborhoods using Geographic Weighted Regression and Ordinary Least Squares regression showed that three variables—the mixed residential-commercial per capita land use, the rate of students, and the rate of unemployed individuals—accounted for 40% of COVID-19 prevalence in these neighborhoods. In fact, analyzing the effective factors in the spread of COVID-19 in the neighborhoods of Qom provided comprehensive insights that could be considered for preventive measures.

Keywords: COVID-19, Geographic Information Systems (GIS), Iran, Qom city, Regression analysis, Spatial analysis

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1. Introduction

With the outbreak of COVID-19 and the death toll surpassing 1,000 in 2019, national and international organizations have increasingly focused on health and disease issues in cities and residential areas. As of May 18, 2024, nearly seven million people worldwide and 147,000 in Iran have lost their lives due to this disease [1]. The United Nations believes that if this crisis is neglected, millions of people will become infected and could potentially lose their lives [2].

The SARS-CoV-2 virus has been recognized as the ninth coronavirus to infect humans and the seventh known coronavirus in the past twenty years [3]. Studies confirm that bats are the primary reservoir of the virus; however, the intermediate source of the virus and its transmission to humans are still unknown [3, 4].

The first reports of coronaviruses' pathogenicity date back to the 1920s [5]. In 2012, a new beta-coronavirus was identified in Jeddah, Saudi Arabia. In 2019, a new case that caused pneumonia was reported in Wuhan, China [3]. These instances indicate that diseases such as COVID-19 and various pandemic outbreaks have existed throughout history, and it is the urban planners' and city managers' decisions that determine the level of human communities' preparedness to accept and cope with its harmful consequences.

Cities, due to their population density, high concentration of buildings, and human interactions, are more exposed to health and treatment risk factors than other areas [6]. For this reason, extensive studies on urban health have been conducted for centuries [7]. The outbreak of COVID-19 and the resulting crisis have been examined as an interdisciplinary topic in various fields, with recent studies linking the evolution of coronaviruses affecting humans to high urbanization rates and poultry farming [3].

Researchers consider various factors, including

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geographical and residential risk factors, as well as racial/ethnic and socioeconomic disparities [8], to be influential in the spread of COVID-19. Some have concluded that pre-existing economic, infrastructural, and health issues have affected the vulnerabilities of slum dwellers during the pandemic [9]. Others believe that the percentage of migrants and the educational level of individuals in neighborhoods influence the spread of COVID-19 [10]. Various researchers have also examined other factors, such as population density, the number of hospital beds, the population over 65, diabetes rates, South Asian migrants, Western migrants, Arab migrants, mortality rates, the number of doctors and nurses [11], and the impact of social-economic factors and essential services on the spread of COVID-19 [12].

Although Qom in Iran [13] and Wuhan in China are officially recognized as the first epicenters of the disease, it must be acknowledged that prior to this, the disease existed unnoticed in other locations [14]. Accepting this point, we must say that, similar to other natural and human disasters, the outbreak of pandemics in population centers can occur at any time. It is the responsibility and mission of urban planners and managers to enhance urban resilience and take preventive measures in this regard.

Today, urban neighborhoods, as the smallest planning units in cities, need to receive more attention than ever. In this context, using various information technology methods, such as Geographic Information Systems (GIS), will be useful as a suitable tool for understanding and analyzing different indicators, facilitating the visualization and management of geographic spatial information and phenomena's spatial relationships [15]. This approach has so far not received enough attention from urban management researchers, especially in Iran. This study aims to understand the impact of environmental factors on the prevalence of COVID-19 in the neighborhoods of Qom City, examining the effects of each factor on the spread of COVID-19 in urban neighborhoods using Ordinary Least Squares (OLS) regression. By answering these questions and identifying risk clusters, it may be possible to predict the susceptible populations that could be infected in the future and estimate the incidence of the disease. By identifying high-risk neighborhoods and populations, improving existing facilities, and developing risk reduction strategies and new healthcare infrastructure, we can contribute to improving living conditions and urban neighborhood development [16].

2. Materials and Methods

This research is a fundamental-applied study using a descriptive-analytical method. The geographic scope of the research encompasses the neighborhoods of Qom city, the seventh-largest metropolis in Iran, with a population of over 1.2 million as of 2016. Of this population, 49% were women and 51% were men. The city's unique position and geography have led it to be recognized as a strategic city [17].

Data related to patients were obtained from the Qom University of Medical Sciences and Health Services. Due to the unavailability of specific addresses for some patients or their locations being outside Qom, information for some patients was excluded from the analysis [45]. Urban neighborhood data were sourced from the Qom municipality, while population and other relevant data were obtained from the 2016 census of the population and housing in Qom from the Provincial Management and Planning Organization [15].

According to cumulative statistics received from the Provincial University of Medical Sciences, 32,729 people were infected with the COVID-19 virus between January 2020 and September 2021, based on patients' addresses and urban neighborhoods. Of this number, 3,747 people (11.45%) lost their lives [45]. This study conducted a total population sampling of the statistical population. As shown in Figure 1, the daily infection trend for COVID-19 peaked in March 2020, September 2020, April 2021, and August 2021.

Next, the data for each patient, along with their residence, demographic, and clinical information obtained from the University of Medical Sciences, were geolocated using ArcGIS software at their residence addresses. Subsequently, the data related to the Population and Housing Census centers were also differentiated for each neighborhood (135 neighborhoods).

In this research, to identify the factors affecting the prevalence of COVID-19 in the neighborhoods of Qom City, based on demographic, social, economic, and geographic indicators, spatial cluster analysis at the neighborhood level was utilized [18, 19]. Additionally, to compile the desired indicators for the study, a total of 98 indicators were initially selected based on the literature review and an examination of 36 related studies. In the next step, through consultations with experts and specialists familiar with the subject, and by eliminating some indicators due to various reasons, such as the lack of access to appropriate data and statistics, the number was reduced to 74 indicators. As shown in Figure 2, 17 indicators were chosen for demographic-social factors, 16 for economic factors, 34 for structural factors, and 7 for comorbidity factors. Given the application of these indicators in other studies and the confirmation by experts familiar with the subject, it can be said that the indicators used in the research possessed the necessary reliability and validity.

In the next step, as shown in Figure 2, each hypothesis of the research was examined using various tests. The correlation of the COVID-19 infection rate in spatial terms at the neighborhood level (the infection rate in the neighborhood, defined as the number of identified patients divided by the neighborhood's population multiplied by one hundred thousand) in Qom City was evaluated based on Global Moran's I statistics, considering weights derived from inverse distance and the proximity of edges and boundaries between neighborhoods [20]. Local Moran's I was then calculated for confirmed cases and the COVID-19 infection rate [21]. The spatial autocorrelation statistics related to each neighborhood in Qom City were assessed based on several surrounding spatial units using GIS software. For each neighborhood, i was calculated using the following formula:

$$I_i = \frac{\sum_j^n = 1\, W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\frac{1}{n}\sum_{j=1}^{n}(y_j - \bar{y})}$$

where y represents the COVID-19 infection rate in the ith neighborhood or its jth neighboring neighborhood, and Wij denotes the weight indicating the adjacency of neighborhoods I and j (in this case, the inverse distance between them). Consequently, the locations of statistically significant spatial clusters and outlier points can be identified, displayed on maps, and examined. These clusters are termed High-High (high values surrounded by high values or hot spots) and Low-Low (low values surrounded by low values), while outlier points include High-Low (high values surrounded by low values) and Low-High (low values surrounded by high values).

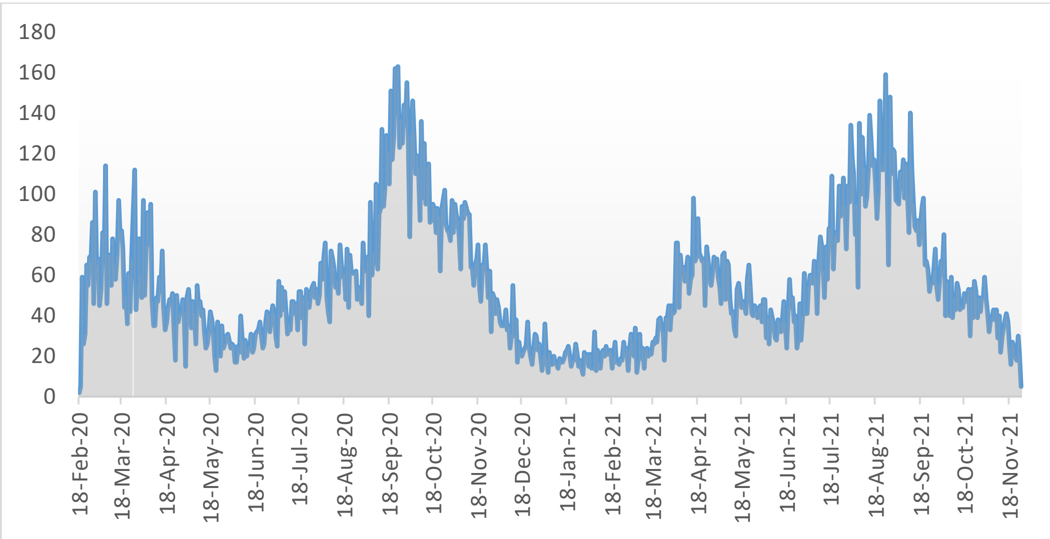

Figure 1. Source: Statistical data on COVID-19, Qom University of Medical Sciences, 2024

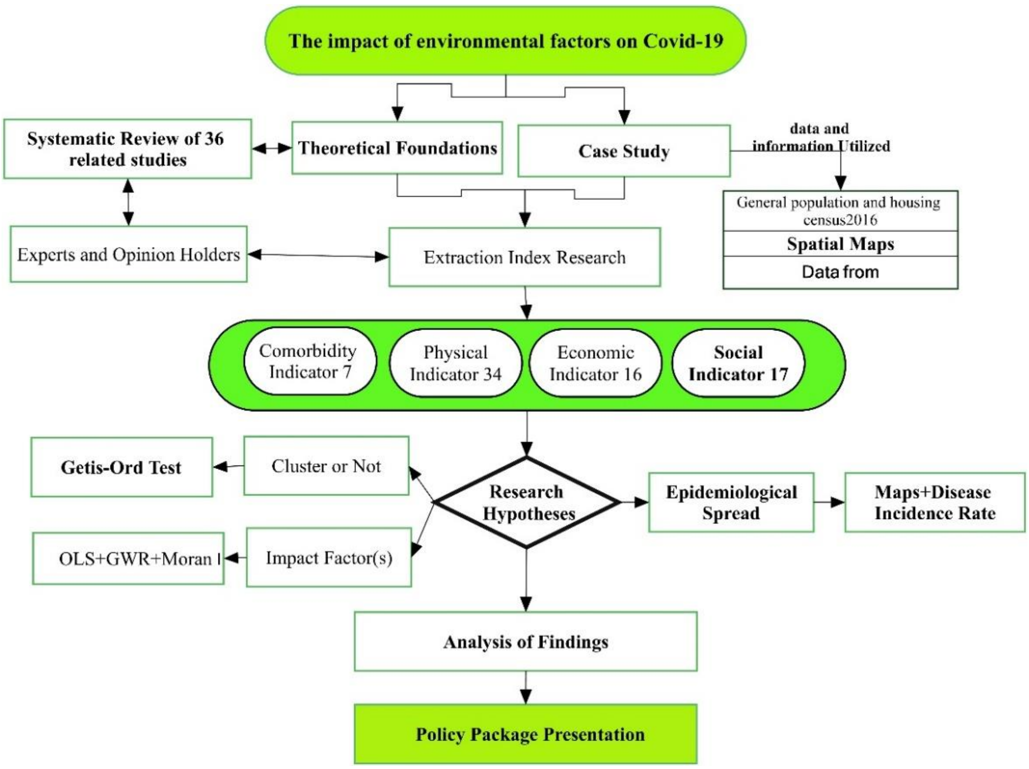

Figure 2. Research implementation process
Source: Research findings, 2024

Subsequently, regression analysis was utilized. Regression methods are widely used in health-related studies. One of these methods is OLS regression, which is employed to reveal the strength of relationships between dependent variables and the most important explanatory variables during the time period under study [23]. This regression is also used to predict or model a dependent variable in relation to a set of explanatory variables [27]. In this study, the COVID-19 prevalence rate in the neighborhoods of Qom city during the period examined was defined as the dependent variable. Each of the indicators under consideration was then examined separately. This ensures that relevant relationships between explanatory variables from each data set are not overlooked. For each data set studied in the research, OLS regression with correlated variables was conducted twice. As previously confirmed in other COVID-19 health studies [24], any variable with a Variance Inflation Factor (VIF) greater than 7.5 was removed [25]. A stepwise method based on the Akaike Information Criterion (AIC) was then employed to reduce both sets of determinants to their non-redundant cores.

Given that data normality is a prerequisite for regression testing, the research data were examined using SPSS software and the Kolmogorov-Smirnov test. Based on the test results and a significance level greater than 0.05, it can be concluded that all the data examined in this research were normally distributed [26].

After running the OLS model, the residuals of the model are calculated. If there is no autocorrelation, the model is accepted, and the actual results are derived from it. The null hypothesis indicates the absence of autocorrelation, while the alternative hypothesis indicates its presence. If one of the spatial error tests with spatial lags is significant, we run one of them. If none of the tests can confirm the null hypothesis, the model is still accepted, and the OLS results are considered valid. However, if neither is significant, we must replace it with Robust LM-lag or Robust LM-error, following the same procedures as the previous tests.

On the other hand, considering the existence of spatial data in the research, Geographically Weighted Regression (GWR) was used as a tool to examine the OLS hypotheses, which assume that the observations and error terms within the study area are independent and stationary [22]. In this method, a kernel function with a bandwidth parameter is used to calculate a matrix of local weights in terms of the distance between each pair of spatial units. Taking i = 1,…,n as each sample neighborhood, the GWR is mathematically represented as [28]:

$$y_i = \beta_{i0} + \sum_{k=1}^{p-1} \beta_{i0} X_{ik} + \varepsilon_i$$

where yi is the dependent variable representing the confirmed COVID-19 cases in neighborhood i, xik is the value of the kth explanatory variable in the neighborhood i, βi0 is the intercept, βik is the regression coefficient for the kth explanatory variable, p is the number of regression conditions, and εi is the random error at location i. Cumulative count data in COVID-19 studies have been used, particularly at small-scale levels, such as neighborhoods or counties.

Ultimately, the statistical performances of OLS and GWR were compared. Hence, the reduced set of determinants was considered based on data obtained from January 2020. We then determined how GWR outputs explained the COVID-19 prevalence in each neighborhood, as well as how each relevant factor influenced the emergence of hotspots for new cases. Considering the spatial context, an adaptive Gaussian kernel function was selected to adjust weights for infection density. Finally, to examine whether there is spatial dependence in the GWR residuals, the Global Moran's I test (variance inflation factor) was applied to them. Weights were once again based on the adjacency of edges and boundaries among neighborhoods [20]. Spatial analysis and OLS regression were conducted using ArcGIS 10.8.1 software in this research.

3. Results

As shown in Figure 3, the prevalence rate (the prevalence rate is defined as the number of COVID-19 cases divided by the neighborhood population, multiplied by 100,000) of COVID-19 in neighborhoods of Qom city can be categorized into five groups. Accordingly, only the Amin-Saheli neighborhood had the highest COVID-19 prevalence, followed by the neighborhoods of Mosalla, Doorshahr, Zad, and Nekuyi, which had a prevalence rate ranging from 10-25 thousand cases per hundred thousand people. In other words, in these neighborhoods, the infection rate of this disease was between 10% and 24%.

Clustered and Non-Clustered Indexes

In this section, the presence or absence of spatial autocorrelation in the study's spatial units was assessed, and based on the Getis-Ord test, the hot and cold spots of disease prevalence in neighborhoods of Qom City were identified. As illustrated in Figure 4, among the 33 indicators examined, such as nationality (Iranian and non-Iranian), the gender of the infected person (male and female), time of infection (seasons of spring, summer, autumn, and winter in the years 2019, 2020, and 2021), age (under 15, 15 to 65, and over 65 years), pre-existing conditions (cardiovascular diseases, respiratory diseases, kidney diseases, diabetes, taste disorders, ageusia, immune deficiencies, and pregnancy in women), year of diagnosis (2019, 2020, and 2021), and observed symptoms (fever, body aches, sore throat, abnormal radiology findings, cough, shortness of breath, headache, and diarrhea), only certain comorbidity indicators (Ageusia, taste disorders, immune deficiency diseases, and those with abnormal radiology findings), the non-Iranian nationality, pregnancy status for women infected with COVID-19, and finally, the mortality rate were found to be similar to the mentioned figure, while 28 other indicators showed the same hot neighborhood conditions. In other words, for the 28 indicators examined, the neighborhoods of Salarieh, Zeynabiyeh, Jahanbini, Amin Boulevard, Saheli, and Mosalla were among the hot neighborhoods or High-High clusters (meaning high values surrounded by high values). In the other neighborhoods, the results were not significant.

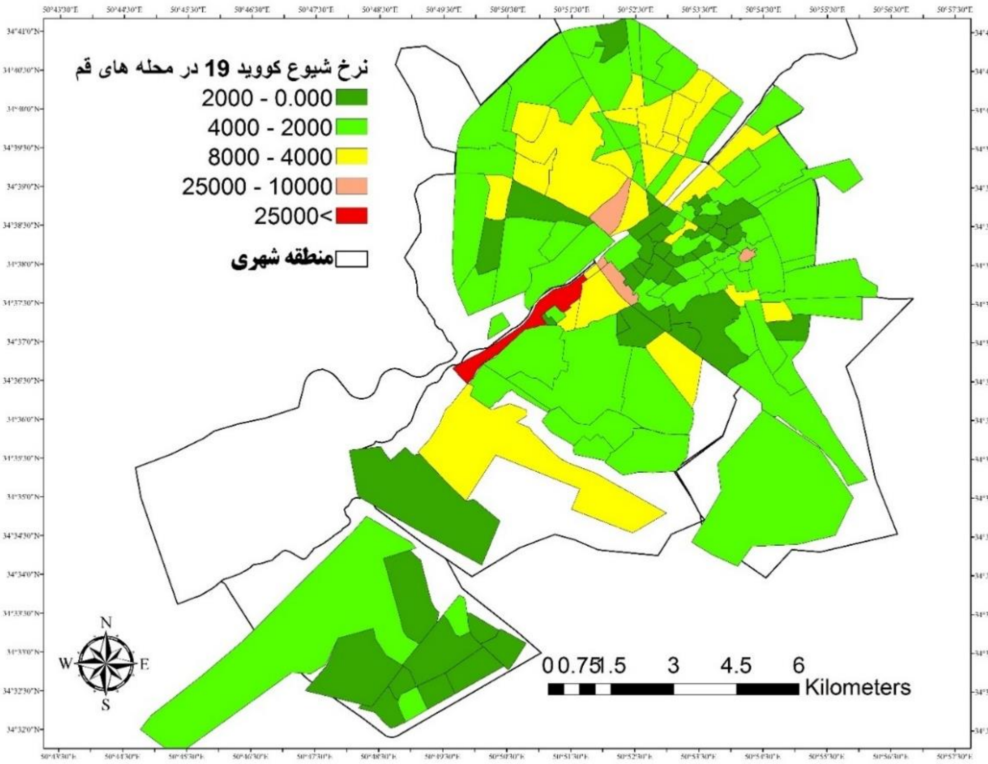

Figure 3. COVID-19 prevalence rate in neighborhoods of Qom City
Source: Research Findings, ArcGIS Software Output, 2024

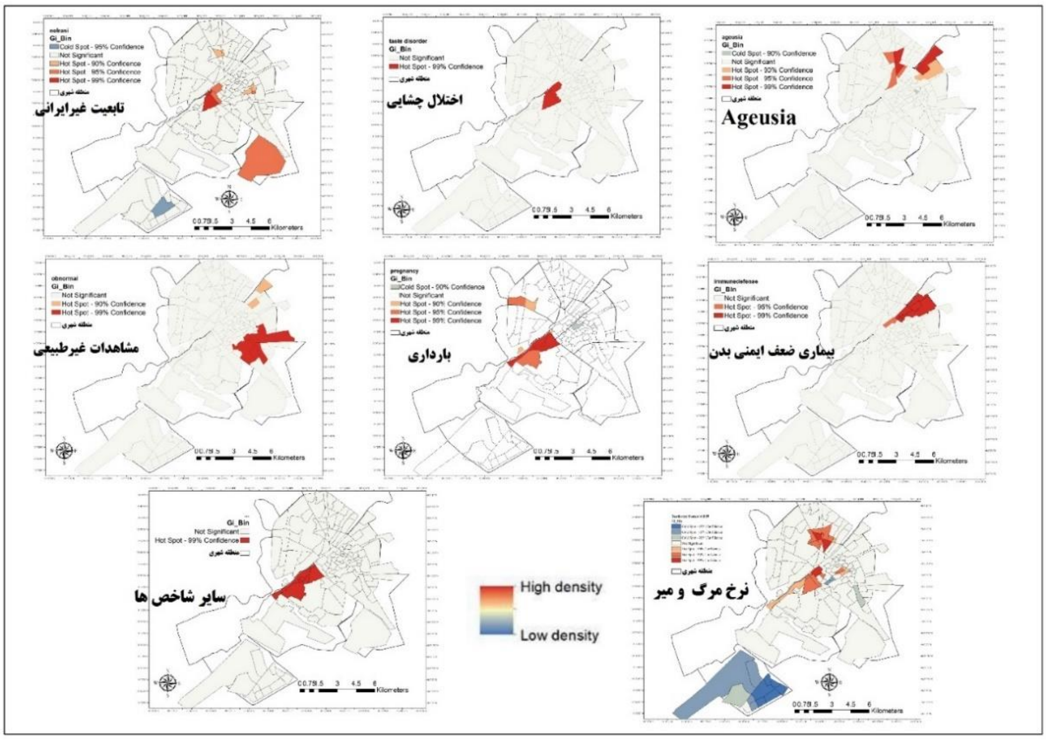

Figure 4. Spatial cluster analysis of the cumulative frequency of COVID-19 outbreaks based on the indicators studied
Source: Research findings, Getis Ord test output in ARC GIS environment, 2024

However, in seven other indicators, hot neighborhoods similar to the aforementioned figure were identified. Additionally, the neighborhoods of Safaieh, Sheikh Nayeb, and Esmailabad exhibited the highest density (hot spots) regarding COVID-19 mortality. In fact, the neighborhoods of Bakayi, Mosalla, Doorshahr, Safaieh, Manba' Ab, Jamkaran, Razaviyeh, Dar Behesht, Gandarmha, and Esmailabad were identified as hot spots due to the presence of non-Iranian nationals and immigrants or their proximity to these populations.

In terms of taste disorders, the neighborhoods of Bakayi, Mosalla, Doorshahr, and Safaieh were noted, while for ageusia, the neighborhoods of Bajak 2 and 3, Chahar Imamzadeh, Hanif Nejad, Sheikh Nayeb, Tolid Daru, Gandarmha, and Esmailabad were identified. For immune deficiency cases, Bajak 1 and 2, Chahar Imamzadeh, Amaryasir, Baghe Panbeh, Tekyeh Agha, Arabestan, and Eram were highlighted. Moreover, neighborhoods such as Salakh Khaneh, Sarajeh, Mahdieh, Golzar, Bagh Karbasi, Majidieh, Zaviyeh, Bajak 3, and Chahar Imamzadeh were identified as hot neighborhoods based on abnormal symptoms in COVID-19 patients. The prevalence rate of the disease and the mortality rate across neighborhoods indicated certain differences. Mortality rates were higher in less affluent neighborhoods, whereas the prevalence of COVID-19 was higher in affluent neighborhoods, which also contained greater densities.

Impact of Environmental Components on COVID-19 Prevalence in Neighborhoods of Qom City

In this section, the impact of five components (including 74 indicators) on the prevalence of COVID-19 was examined using the OLS regression test.

The sociodemographic component included ten indicators of vulnerable age groups (the proportion of individuals aged 0 to 14 years, the proportion of women aged 50 and older, and the proportion of individuals aged 65 and older), population density, literacy status of the population aged 6 and older (literate and illiterate), student population (students studying domestically and abroad), marital status (married, widowed due to death, single due to divorce, never married, previously married at least once), age of patients (under 15, 15 to 65, and over 65 years), gender of patients (male and female), and nationality (Iranian and non-Iranian).

The economic component included indicators related to housing type (living in an apartment, living in a non-apartment unit, living in a conventional house), materials of the residential unit (brick and iron, wood and brick, cement block, or all-brick or stone and brick), lower economic groups (net density of units up to 50 square meters and 50 to 100 square meters, and rental rates), upper economic groups (net density of residential units with an area of 100 to 200 square meters and more than 200 square meters, and ownership rates), and employment status (employed, unemployed, and individuals with income without a job).

The environmental-land use component included 26 land use types per capita in each neighborhood. The underlying conditions (comorbidities) examined included chronic diseases, such as respiratory diseases, vascular diseases, diabetes, kidney diseases, liver diseases, malignancies, immune deficiencies, and pregnancy in women with COVID-19. Additionally, the symptoms exhibited by each individual infected with COVID-19 included chills, body temperature, body aches, taste disorders, cough, diarrhea, shortness of breath, sore throat, and abnormal radiology findings.

After various examinations and repeated tests using ArcGIS software with OLS, we concluded that among all the indicators studied, only three indicators—the rate of students, the rate of individuals with income without a job for over ten years, and the mixed residential-commercial per capita in urban neighborhoods—had a significant relationship with the cumulative prevalence rate of COVID-19 in urban neighborhoods.

As indicated in the summary tables of the OLS results (Table 1 and Table 2), the Probability and Robust_Pr results for all three indicators were significant. In other words, the significance of these variables showed that the independent variable was important in predicting the dependent variable. To determine if any additional variable was omitted from the results, the Variance Inflation Factor (VIF) was considered, which should be less than 7.5. Given that this number is smaller in the results of the test in question, it can be concluded that no other side variables were included in the results of this test.

Table 1. Summary of OLS results

Variable	Coefficient [a]	Std Error	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Rate of students in neighborhoods	-0.145	0.041	3.488	0.000*	0.065	2.247	0.026*	1.469
Rate of people with income without a job for over ten years in neighborhoods	0.614	0.163	3.765	0.000*	0.176	3.482	0.000*	1.273
Mixed residential commercial per capita	674.676	144.933	4.655	0.000*	190.362	3.544	0.000*	1.382

Source: Research findings, OLS test output in ARC GIS software environment, 2024

Table 2. OLS results

Input Features:		Dependent variable	Patient rate
Number of observations	136	Akaike's Information Criterion (AICc) [d]:	2643.402
Multiple R-Squared [d]:	0.4319	Adjusted R-Squared [d]:	0.4100
Joint F-Statistic [e]:	19.7700	Prob(>F), (5,130) degrees of freedom:	0.000000
Joint Wald Statistic [e]:	141.220	Prob(>chi-squared), (5) degrees of freedom:	0.000000
Koenker (BP) Statistic [f]:	15.512	Prob(>chi-squared), (5) degrees of freedom:	0.008382
Jarque-Bera Statistic [g]:	4.583	Prob(>chi-squared), (2) degrees of freedom:	0.1010

Notes on Table Interpretation:
*A star next to a number indicates that the P-value is statistically significant (P<0.01).
[a] Coefficient: Indicates the strength and type of relationship between each independent variable and the dependent variable.
[b] Probability and Robust Probability (Robust_Pr): A star (*) indicates that a coefficient is statistically significant (P<0.01); if the Koenker statistic (BP) [f] is statistically significant, use the Robust Probability column (Robust_Pr) to determine the coefficient.
[c] Variance Inflation Factor (VIF): Large values of the Variance Inflation Factor (VIF) (>7.5) indicate redundancy among independent variables. This number should be less than 7.5.
[d] R-Squared and Akaike's Information Criterion (AICc): Model fit/performance metrics.
[e] Overall F and Wald statistics: A star (*) indicates the overall significance of the model (P<0.01); if the Koenker statistic (BP) [f] is statistically significant, use the Wald statistic to determine the overall significance of the model.
[f] Koenker Statistic (BP): When this test is statistically significant (P<0.01), the modeled relationships are not compatible (due to either non-constancy or heteroscedasticity). To determine the significance of the coefficient, rely on Robust Probabilities (Robust_Pr), and for the overall significance of the model, rely on the Wald statistic.
[g] Jarque-Bera Statistic: When this test is statistically significant (P<0.01), the predictions of the model are biased (the residuals are typically not normally distributed).
Source: Research findings, OLS test output in ARC GIS software environment, 2024

As mentioned in the guide for Table 2, the fit/performance metrics for this model were equal to 0.4319. On the other hand, due to the significance of the Conker statistic, the Wald statistic was used to determine the overall importance of the model. The results of the test showed that the obtained score was 141.220, with a significance level of 0.000.As highlighted in the guide for Table 2, the significance of the Jarque-Bera statistic indicated that the model's predictions were biased, and it was necessary to test other indices. However, as shown in Table 2, since the result of this statistic was not significant here, it can be claimed that the examined indicators performed well in predicting the dependent variable. Furthermore, the significance of the Conker statistic indicated that the column Robust_Pr in Table 2 should be trusted. In conclusion, and given the significance of this column, it can be stated that the three variables—the rate of students, the rate of individuals with income without a job for over ten years, and the mixed residential-commercial per capita in urban neighborhoods—accounted for 43% of the COVID-19 infection rate.

The next step to confirm the results of this statistic involved examining the standardized residuals (STD Redu). If the spatial autocorrelation of Moran's I for this variable is clustered, it means that the OLS test has not adequately fitted the model. Figure 5 shows the results of Moran's residual autocorrelation test. As demonstrated in section (a), the autocorrelation of the residuals was random, and section (b) indicated that the Moran index was equal to 0.038 and the expected index was -0.007 with a variance of 0.003, which was not significant. Therefore, it can be said that the STD Redu of this test was also randomly distributed at the neighborhood level in Qom City. Thus, the results of the OLS test in this research can be trusted.

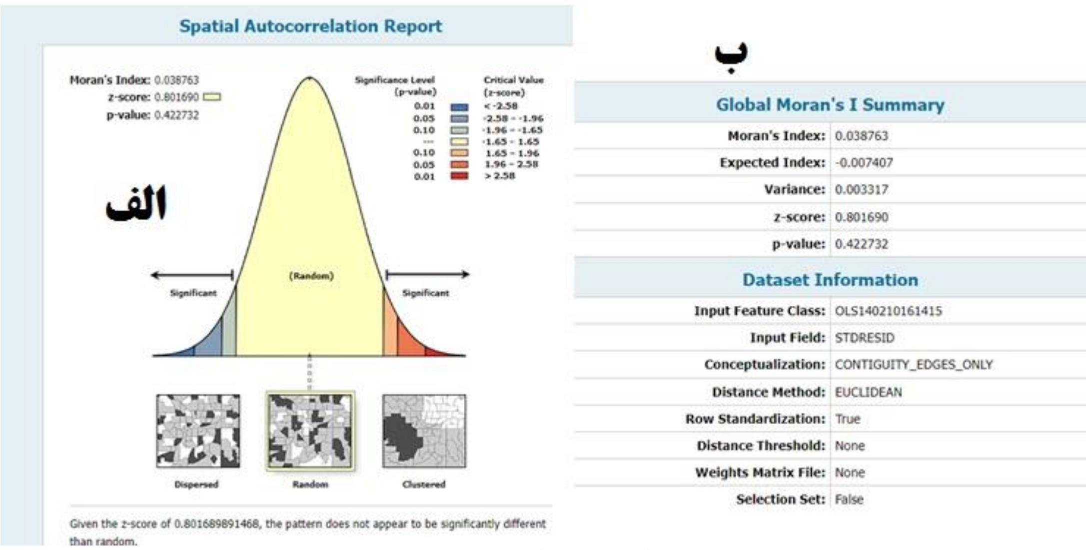

Figure 5. Moran's spatial autocorrelation report I
Source: Research findings, Moran I test output, in ARC GIS environment, 2024

The next step was to plot the variable matrix and determine their linear process. As shown in Figure 6, with an increase in the mixed residential-commercial per capita rates and the rate of individuals with income without a job, the rate of COVID-19 patients in urban neighborhoods also increased. Conversely, there was a negative relationship between the rate of students (the presence of students correlated with schools being open). The research only examined statistics and data related to students and the COVID-19 infection rate in urban neighborhoods. This means that as the rate of students in a neighborhood increased, the COVID-19 infection rate decreased. In other words, a higher number of students signified greater awareness among citizens regarding the spread of the disease. These individuals, by obtaining information and communicating it to their families, help prevent further spread of the illness.

The variable "the rate of individuals with income without a job for over ten years in the neighborhoods of Qom City" indicated a significant relationship between this variable and the prevalence of COVID-19 in urban neighborhoods. In other words, as the number of such individuals in the neighborhoods increased, the prevalence of the COVID-19 virus also rose in these areas. To analyze this, it is essential to first identify the target audience of this variable. This group included retirees, the disabled, financial market speculators, and individuals with high financial capacity who invested in various sectors and made a living from the profits of their investments. Given the leisure time of this group, we can expect greater interaction with different groups and peers. This suggests a lack of compliance with regulations related to disease outbreak precautions by this group. It can be concluded that the higher the rate of individuals with income without a job for over ten years in urban neighborhoods, the fewer health regulations will be observed, resulting in an increased prevalence of the disease in these neighborhoods. The mixed residential-commercial per capita index referred to buildings that served dual purposes, where commercial and residential activities occurred simultaneously. Supermarkets, retailers, and similar establishments belonged to this category. Typically, these stores were subjected to less inspection regarding compliance with health regulations, leading to minimal health care measures in these units. If the per capita of this land use was higher in urban neighborhoods, the prevalence of COVID-19 would also be greater in those areas. This indicated a widespread connection among the residents of the neighborhood through these small-scale commercial units.

In summary, if we want to examine these indices together and assess the impact of these three indicators on the prevalence of COVID-19 in urban neighborhoods, we use GWR. As shown in Table 3, the three independent variables—mixed residential-commercial per capita, the rate of individuals with income without a job, and the rate of students in the neighborhoods of Qom City—accounted for 40% of the COVID-19 infection rates in urban neighborhoods. In fact, with proper planning based on these three indicators, up to 40% of the disease prevalence in neighborhoods can be controlled.

Sigma: This is the index of the standard deviation of the residuals, and a smaller value indicates a superior model.

Akaike: This is a very useful index for comparing regression models, where a lower value indicates a better fit of the model to the observational data.

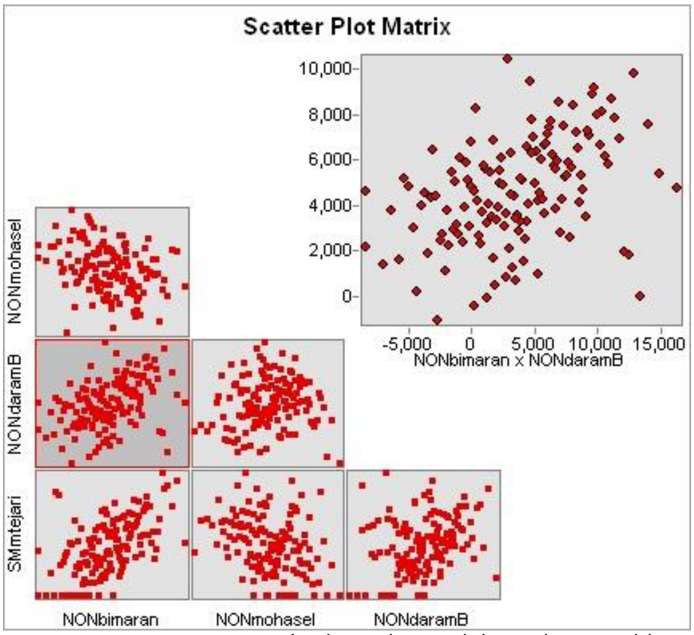

Figure 6. Matrix of independent and dependent variables
Source: Research findings, OLS test output in ARC GIS software environment, 2024

Table 3. Results of the geographical weighted regression test of the variables under study

Variable name	Residual Squares	sigm	AICc	R2	AdjustedR2
Variables under investigation	2067442201.72	3957.72	2645.44	0.404	0.390

Source: Research findings, GWR test output in ARC GIS software environment, 2024

4. Discussion

The aim of the present research was to identify the components affecting the prevalence of COVID-19 in the neighborhoods of Qom city, where statistical information about COVID-19 cases from 2019 to 2021 and other environmental and economic characteristics of Qom neighborhoods (74 indices) were analyzed using ARC GIS software. The first objective of the research was to determine the COVID-19 infection rate in the neighborhoods of Qom City. For this purpose, after calculating the infection rate of COVID-19 in urban neighborhoods, the spread of COVID-19 was mapped using ARC GIS. It was found that the COVID-19 infection rate in the neighborhoods of Qom City was not uniform, with some neighborhoods showing infection rates exceeding 10%, while neighborhoods in regions 1, 5, and 8 had an infection rate of less than 4%.

Another objective of the research was to assess how the indicators of interest were concentrated in the neighborhoods of Qom City. The findings indicate that among the 33 indices studied, in 25 of them, only the neighborhoods of Mosalla, Bakayi, Jahanbini, Zeynabiyeh, Salariyeh, and Amin Boulevard in the southwestern part of Qom City were identified as hot spots. In other words, in these neighborhoods, the spatial units showed spatial autocorrelation with high values clustered together. However, for the indices of non-Iranian citizenship, pregnancy, taste disorders, ageusia, unnatural observations, and mortality rates, the hot spots identified in the neighborhoods were different.

The third objective of the present research was to examine the impact of environmental factors on the spread of COVID-19 in urban neighborhoods. To this end, 74 indicators were evaluated. Geographically Weighted Regression and OLS regression were selected as the regressions to investigate the explanatory variables. Initially, OLS regression tests were conducted for each indicator and the COVID-19 spread rate in the neighborhoods of Qom City. The results of this test indicated that only three indicators—the per capita mixed residential-commercial land use, the rate of students, and the rate of individuals with income without a job—had a significant impact on the COVID-19 spread rate in the neighborhoods of Qom City. Among these, the mixed residential-commercial per capita land use had the greatest effect on the spread of COVID-19. Subsequently, the indicators of the rate of individuals with income without a job and the rate of students also influenced the COVID-19 spread in the neighborhoods of Qom City. It was also found that there is a negative correlation between the student rate in the neighborhoods and the COVID-19 spread rate.

By comparing the findings of the present study with other related studies, it was found that the results of this research aligned with those of Eisa Zadeh et al. [29] in terms of the variation in the spread and mortality rates of COVID-19 across urban areas and different provinces. Additionally, the clustering pattern of COVID-19 spread in the areas of Qom City was in line with the research of Jaziri et al. [30]. The distinction of this study lies in its neighborhood-level analysis, leading to this conclusion. Further supporting the findings of Nikpoor et al. [31], it was concluded that male gender, older age, and comorbidities had a significant correlation with the spread of COVID-19. Similarly, in agreement with Nasiri et al.'s research, it was determined that the spread of COVID-19 had a significant relationship with the place of residence, underlying diseases, and the type of land use surrounding the patients' residences. In areas with high population density and areas with commercial and residential use, the number of patients was high, and there was a direct relationship between them [32]. The neighborhood-oriented perspective is another innovation of this research.

Although studies like Yee Han's [33] have concluded that population density impacts the spread of COVID-19, this point was not confirmed in the present study. It was further clarified that mixed residential-commercial per capita land uses had a significant correlation with the COVID-19 spread rate in urban neighborhoods. This perspective aligns with other studies [34-36], which posits that social and economic conditions (such as housing density, urban neighborhoods, occupational characteristics, migration, gender, age, race/ethnicity, income, occupational hazards, low-income apartments, low-mobility communities, and minorities) influence the spread of diseases.

In other words, in the OLS tests, among the 74 indicators examined, only mixed residential-commercial per capita land use, the rate of individuals with income without a job, and the rate of students were found to affect the spread of COVID-19 in urban neighborhoods. In fact, among various land uses, only mixed residential-commercial per capita land use had the strongest correlation with the spread of COVID-19. This means that even when preventive governmental measures were implemented, and some land uses were mandated to adhere to health guidelines or lockdown, mixed residential-commercial land uses remained operational, and people continued to frequent these spaces. These land uses included grocery stores, retail shops, and small services for citizens. This observation was consistent with other global studies, and it seems logical that bustling places in urban neighborhoods, such as shops, supermarkets, clinics, and administrative offices, are frequented by people to meet their needs. Therefore, these spaces are identified as areas for the spread and proliferation of the disease.

Therefore, this research aligns with the findings of Martinez et al. (2021), Coc et al. (2021), and Pan et al. (2021) in suggesting that urban spaces and per capita figures should be taken into account [37-39]. Since these land uses and urban spaces influence the spread of COVID-19, it is necessary to consider them in urban management. Investigations show that during the COVID-19 outbreak, retail stores, restaurants, and other businesses remained operational, and health regulations were not strictly enforced on them [40]. As some have stated, commutations related to obtaining family necessities were among the most frequent daily journeys [41].

Some studies have indicated that families with lower incomes were more vulnerable in the face of the COVID-19 virus [42]. Indeed, some believe [43] that the pandemic led to job loss, reduced income, and economic uncertainty, significantly affecting low-income populations and increasing income inequality. This research concluded that occupational groups and individuals with income without a job influenced the spread of COVID-19 in urban neighborhoods. In fact, GWR incorporates spatial autocorrelation and allows for relationships between variables to vary in space and be defined for each location [44].

5. Conclusion

Among the limitations of this study, one can mention the absence of a neighborhood-level perspective, resulting in a lack of comprehensive neighborhood-specific data, the unavailability of information on all individuals infected with COVID-19, and the unclear origins and true source of the disease in the world and in Qom city. It is anticipated that if other researchers focus on urban health at the neighborhood level, the experiences from such studies can contribute to the resilience of cities. This research believes that the spread of pandemics can occur at any time, and urban managers must plan in a way that ensures preparedness for similar crises. Just as we prepare cities for earthquakes and other natural disasters, we must also plan for social and health crises. Ultimately, it is urban management that decides whether a city is safe for its residents or not.

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Authors' Contribution

All authors had a common contribution.

Competing Interests

The authors hereby declare that there are no conflicts of interest regarding the present research.

Ethical Approval

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