Journal of Data Applications
Issue: 1, 2023
E-ISSN: 2980-3357

RESEARCH ARTICLE

Istanbul's Community Mobility Changes During the COVID-19 Pandemic: A Spatial Analysis

Ahmet Okan ARIK[1], Gülsüm Çiğdem ÇAVDAROĞLU[2]

ABSTRACT

COVID-19 was the most recent pandemic to strike humanity. Moreover, this pandemic occurred during the most active period of global interaction and mobility, unlike pandemics like cholera, plague, and flu in earlier centuries. Many countries restricted domestic mobility after suspending international mobility to prevent the pandemic from spreading. Although these policies differ from nation to nation, they have affected the mobility of communities. This study examined spatial and non-spatial independent variables that affected how the community's mobility patterns changed in various locations, including parks, transit stations, workplaces, grocery and pharmacies, and residential areas in Istanbul, Türkiye. The impact of the independent spatial variables on the mobility changes was examined after identifying the non-spatial independent variables influencing the mobility changes in 6 different areas. It was determined that the altitude variable, expected to impact how mobility changed, had no overall impact on the dependent variable. On the other hand, the dependent variables representing the mobility changes were affected by the independent variables representing the county center's latitude and longitude values and whether the county is located near the sea. Regression analysis across Türkiye will be performed in upcoming studies using an updated version of the methodology used in this study.

Keywords: Urban Mobility, Mobility Analysis, Spatial Analysis, COVID-19, Google Community Mobility Report

DOI: 10.26650/JODA.1215566

[1]Istanbul University, Institute of Science, Department of Informatics, Istanbul, Turkiye
[2]Işık University, Faculty of Economics, Administrative and Social Sciences, Information Technologies, Istanbul, Turkiye

ORCID: O.A.A. 0000-0002-4875-4800; G.Ç.Ç. 0000-0002-6572-1605

Corresponding author:
Ahmet Okan ARIK,
Istanbul University, Institute of Science, Department of Informatics, Istanbul, Turkiye
E-mail: aokanarik@gmail.com

Submitted: 07.12.2022
Revision Requested: 05.01.2023
Last Revision Received: 19.01.2023
Accepted: 23.01.2023

Citation: Arik, A. O., & Cavdaroglu, G. C. (2023). Istanbul's community mobility changes during the COVID-19 pandemic: a spatial analysis. *Journal of Data Applications, 1*, 1-17. https://doi.org/10.26650/JODA.1215566

Introduction

Due to the new coronavirus's rapid rate of spread and potential danger, the disease was recognized as a global pandemic on March 11, 2020 (WHO, 2020). A highly contagious disease known as COVID-19 is thought to have started in the Chinese city of Wuhan and spread worldwide (Saha et al., 2020). The Omicron variant is currently the dominant variant in rapid circulation, whereas Alpha, Beta, Gamma, and Delta were the previous dominant variants. In addition, the Omicron variant, which spreads more rapidly than the Delta variant, has been found to be a milder form of the disease (Vitiello et al., 2022).

The fact that the vaccines are taken with reminder doses against the dominant variant Omicron and that the total number of vaccine doses administered as of May 7, 2022, was 11,579,263,039 may indicate that the end of the pandemic has recently been approached (Vitiello et al., 2022; WHO, 2022a). However, COVID-19, with its many variants, caused 513,955,910 confirmed cases of COVID-19 and 6,249,700 related deaths globally as of 5:31 pm CEST, May 6, 2022, globally (WHO, 2022a). From January 3, 2020, to May 9, 2022, at 5:13 pm CEST, in Türkiye, 15,043,379 cases and 98,846 deaths were reported, and 147,426,248 doses of the vaccine were administered (WHO, 2022b).

The COVID-19 pandemic has disrupted several areas of life, such as the education sector, which has transformed itself into the online domain, the business life that started with hybrid and remote working, and the changing of shopping habits with the widespread use of online shopping and contactless payment. Another issue that had to undergo changes and restrictions during the pandemic was mobility. Mobility is an inseparable part of people's daily life for required reasons for workplaces, hospitals, and activities such as entertainment and shopping. However, Istanbul has intense mobility as its population is nearly 20 million, and it is an international transit hub due to its geographical location. Therefore, after the start of the pandemic, the Republic of Türkiye, like many countries, restricted both domestic and international mobility with measures such as lockdowns, quarantines, and flight bans in all its provinces, including Istanbul, and banned many community activities such as sports, education, and cultural activities.

This study aims to explain the differences in mobility change rates using the mobility changes dataset enriched with socioeconomic and geographical features. Mobility changes include changes in retail and recreation visit changes, market and pharmacy visit changes, park visit changes, transit station usage statistics, and changes in residence time at workplaces and residences in Istanbul districts between March 2020 and March 2022. By explaining community mobility changes, it is aimed to indicate how the COVID-19 measures taken affected community mobility and the course of the pandemic and to provide policymakers with insight into developing a roadmap for potential pandemics.

Literature Review

Rice & Pan examined the factors affecting park visits at the county level for the early stages of COVID-19. The study depended on Google Community Mobility Reports (GCMR) (Google, 2020). The study revealed that for 97 districts in the western United States, changes in park visits in the spring of 2020 were caused by climate differences due to altitude and latitude. In addition, they point out that counties with older populations and longer stay-at-home orders may be some of the likely reasons for reduced park visits, fear of symptoms among seniors, and county-level travel restrictions. Due to decreased park visits among older people and long-term stay-at-home orders, they recommend examining the relationship between age and stay-at-home orders and park visitation and well-being (Rice & Pan, 2021).

Saha et al. examined the percentages of change in community mobility in India from February 15 to April 30. The dataset for this study was obtained from GCMR. Based on baselines created across India, the results show that workplace mobility decreased by 56.7%, grocery and pharmacy mobility decreased by 51.2%, park visits decreased by 46.3%, and transit station mobility increased by 66%. In addition, retail and recreation mobility decreased by 73.4%. However, lockdowns caused a 23.8% increase in mobility in residential areas (Saha et al., 2020).

Wen et al. examined community mobility and preferred mode of transport at various alert levels using GCMR and Apple maps data. According to the results, the highest-level set, alert level 4, is vital in reducing the quarantined person's mobility and diversity of transport modes. It is stated that the studies carried out to prevent contamination significantly negatively impact retail and recreation mobility. While the use of public transport decreased significantly, it is stated that this was relatively lower in the state of Wellington. It is emphasized that the recovery rate in retail and leisure mobility in the Otago state lags behind other areas. Another contribution of the study to the literature is that the GCMR and Apple maps data used were tested for consistency with the New Zealand Transport Agency data, confirming that they represented the entire population (Wen et al., 2022).

Sulyok & Walker investigated the relationship between the volume of COVID-19 cases and GCMR data and social activity and community mobility. It is stated that after COVID-19 became a global situation, mobility decreased. This decrease may be due to legal restrictions or people's fear of the disease. Sulyok & Walker stated that the decrease in mobility in some countries before legal restrictions reveals the importance of personal infection risk and behavior change. It is stated that it can be understood by cultural, social, and economic factors (Sulyok & Walker, 2020).

Many datasets made available during the COVID-19 pandemic have made it possible to analyze community mobility dynamics and spatial distribution throughout the quarantine. Beria & Lunkar used the "Italy Coronavirus Disease Prevention Map package" data produced by Facebook in their studies. The first of the questions the authors seek to answer is to what extent people stay at home. The findings show that people with mobility ratio and range of motion are significantly reduced. In the second research question, the mobility of the people before the quarantine period was examined. According to the results, it is stated that some of the population preferred to go abroad to avoid restrictions most of the non-local travel is to neighboring provinces and long travel is below the usual statistics. In the final stage, the position of people during the lockdown was examined. According to the results, it is stated that the population has decreased starting in the northern provinces, especially in the big cities, and the population has been directed toward rural areas (Beria & Lunkar, 2021).

Aloi et al. examined the effects of quarantine measures, which went into effect on March 15, 2020, on urban mobility in Santander, a city in northern Spain. The study collected data from traffic meters, intelligent transport systems data, traffic camera records, and environmental sensors compared with the travel flows and durations before and during the quarantine. According to the study's findings, mobility, the use of public transportation, NO2 emissions, and traffic accidents all decreased by, respectively, 76%, 93%, 60%, and 67% (Aloi et al., 2020).

Bonaccorsi et al. examined the effects of the measures taken to combat the COVID-19 pandemic in Italy on the socioeconomic circumstances of Italian citizens. Mobility restrictions are modeled as an exogenous shock akin to a natural disaster, and a large dataset of human mobility can be examined in real time. It has been observed that the effects of lockdown measures are higher in municipalities with high financial capacity. Furthermore, it is stated in the study that the decrease in mobility is more substantial in municipalities where inequality is higher than in others and per capita income is lower. According to these results, the authors state the necessity of fiscal policies targeting poverty and inequality (Bonaccorsi et al., 2020).

Chan analyzed which features are associated with decreases in mobility for Canada during the COVID-19 outbreak based on Facebook's data (Movement Range Maps). According to the study, there were significant differences in the degree of social distancing in April compared to before February. Another socioeconomic finding is that people who live in multi-flat buildings are less mobile than those who do not. Those with more challenging living conditions are less likely to stay home during a pandemic (Chan, 2020).

Chang et al. (2020) examined human mobility and connectivity during the COVID-19 outbreak in Taiwan in collaboration with Facebook's "Data for Good". Different provinces were determined as density points. The study on these points states that urban travel discounts have more impact than intercity travel discounts due to the risk of pandemics. Furthermore, it is stated that the findings can direct future disease surveillance and travel restrictions in-laws after the controls are eased (Chang et al., 2020).

Wielechowski et al. conducted province and voivodeship level analysis of the COVID-19 pandemic's impact on Poland's public transportation mobility**.** Data sources included the Oxford COVID-19 Government Response Tracker, GCMR, and Polish Ministry of Health data. The study's findings, which account for March 2 and July 19, 2020, demonstrate that Poland's public transportation mobility barely changed. Moreover, there is a strong, negative, and significant correlation between changes in mobility in public transportation and the COVID-19 measures implemented by the Polish government. In conclusion, it has been demonstrated that the government's efforts to stop the pandemic's spread decreased Poland's mobility and increased social distance (Wielechowski et al., 2020).

Orro et al. examined the impact of COVID-19 on urban mobility. The authors examined the change in the number of passengers on a line basis, the use of stops, public transportation supply, duration, and reliability of the A Corua city bus network in Spain, stating that this effect varies depending on the type of public transportation used. The data set includes information on bus boarding, intelligent card usage, and automatic vehicle location. The study's findings indicate that the pandemic significantly impacts public transportation more than other types of traffic. According to the statement, this could result from reduced public transportation, reduced traffic, suspension of street parking fees, easy parking, or fear of contamination. The number of passengers decreased to between 6% and 20% of the reference values during the quarantine period, while the use of public transportation stations near shopping centers and universities was almost eliminated during periods of high cases, while the use of stations nearby in other commercial areas was at a low level (Orro et al., 2020).

Materials and Methodology

Study Area

Istanbul is represented as Türkiye's political, economic, and cultural hub. The study region of this study includes 39 districts in Istanbul. The study area is shown in Figure 1.

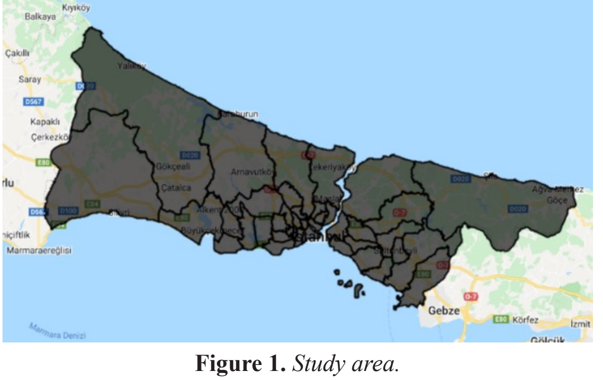

Figure 1. *Study area.*

Data Collection and Preprocessing

Several datasets were used to investigate the factors affecting the changes in the mobility areas in the counties of Istanbul during the COVID-19 pandemic. Since the study’s primary purpose is to examine the spatial and non-spatial independent variables affecting the dependent variables (community mobility variables), the data sets are grouped according to this situation and explained in the following sections. The dataset, source codes, and regression results are also available on GitHub (datastd-dev, 2022). Table 1 summarizes the study’s twelve independent and six dependent variables. The dependent variables will be referred to by the names given in this table in the rest of the study.

Table 1. *Data sets and attributes (D: dependent, I: independent, SV: spatial variable, NSV: Non-spatial variable).*

Type	Name	Data Set Group	Spatial	Explanation	Attributes / Units
D	GCMR	Google community mobility reports	No	GCMR show how visits to places are changing in each geographic region.	Attributes: GP, P, T, RR, R, W. Unit: percentage.
I	SV_1	Elevation	Yes	The elevation of the county center in meters.	Type: numeric. Unit: meter.
I	SV_2	Seaside	Yes	Whether the county is by the sea.	Type: boolean. Values: 0:no, 1: yes.
I	SV_3	Latitude	Yes	Latitude of the county.	Type: numeric.
I	SV_4	Longitude	Yes	Longitude of the county.	Type: numeric.
I	NSV_1	Average Monthly Income (2019-2020)	No	Monthly average household income.	Type: numeric. Unit: TL.
I	NSV_2	Number of Illiterate People (2020)	No	The number of illiterate people aged 6 and over.	Type: numeric. Unit: number of persons.
I	NSV_3	Number of Shopping Centers (2022)	No	The number of the shopping malls.	Type: numeric. Unit: piece.
I	NSV_4	Average Number of Persons in the Household (2022)	No	Average number of people in households.	Type: numeric. Unit: number of persons.
I	NSV_5	Number of Undergraduate and Graduate Graduates (2022)	No	Number of undergraduate and graduate graduates.	Type: numeric. Unit: number of persons.
I	NSV_6	Elderly Population Ratio (2022)	No	Ratio of elderly population to county population.	Type: ratio.
I	NSV_7	Middle Aged Population Ratio (2022)	No	Ratio of middle-aged population to county population.	Type: ratio.
I	NSV_8	Young Population Ratio (2022)	No	Ratio of young population to county population.	Type: ratio.
I	NSV_9	Population Density	No	Population density in the county.	Type: numeric. Unit: percentage.

Figure 2 shows an example view of the dataset.

1	name	SV_1	SV_2	SV_3	SV_4	NSV_1	NSV_2	NSV_3	NSV_4	NSV_5	NSV_6	NSV_7	NSV_8	NSV_9	rere	grophar	parks	transit	work	resi
2	Fatih	29	1	41.0166667	28.9333333	9714	7101	1	3.04	59627	16	53	31	24187	-31.1202	-7.8046	-10.5792	16.5327	-21.4768	6.8907
3	Zeytinburnu	24	1	40.990635	28.89614	6703	4576	2	3.72	32967	10	51	38	23638	-24.7555	21.9448	-16.0055	7.5473	-15.2117	6.2617
4	Güngören	45	0	41.0166667	28.8833333	6232	4395	1	3.42	41836	13	52	35	40042	-18.8974	16.3428	28.3451	14.0693	-18.4372	6.6685
5	Bakırköy	21	1	40.968155	28.8228	16269	1390	8	2.99	75719	21	52	27	7540	-35.918	13.9183	-18.6011	5.9621	-31.0988	8.0785
6	Bahçelievler	68	0	40.9975	28.8505556	8597	9268	3	3.46	99363	11	54	35	34845	-33.8825	10.4852	3.3114	20.5874	-25.1585	7.5423
7	Bağcılar	92	0	41.0455556	28.8405556	5881	13562	3	3.94	69904	8	51	41	17552	-22.082	-7.8537	2.2076	36.295	-18.1038	6.4836

Figure 2. *An example view from the dataset.*

Dependent Variables

Google Community Mobility Reports

GCMR shows the mobility changes in communities throughout the COVID-19 pandemic. Mobility changes in public stations, parks, or specific locations could be detected using these reports. Places, where mobility change could be examined in GCMR are grocery & pharmacies (GP), parks (P), transit stations (T), retail & recreation (RR), residential (R), and workplaces (W).

GP are areas such as markets, pharmacies, and food shops. P provides mobility change in local parks, national parks, dog parks, and public gardens. T provides mobility changes at public stations such as buses, subways, and trains. RR provides mobility changes in restaurants, cafes, shopping malls, libraries, and movie theaters. R denotes the change in mobility in the seats. Finally, W provides mobility change in workplaces. The dates used to determine the reasons for the changes are between March 2020 and March 2022 in the dataset. It is aimed to reveal to what extent the mobility data presented under six different titles are affected by spatial and non-spatial independent variables in this study. For this reason, these six different mobility data will be handled one by one, and the relationship between them and the independent variables explained in the following section will be revealed.

Independent Variables

Community mobility changes based on the counties of Istanbul vary greatly. This study aims to reveal the reasons for these differences. Community mobility can be affected by many independent variables. Therefore, first, it was investigated to what extent the changes were affected by spatial and non-spatial variables. For this reason, independent variables are discussed under two main headings, spatial and non-spatial variables.

Spatial Variables

Spatial variables that affect community mobility changes based on Istanbul counties will be discussed in this section. Some literature studies have revealed that community mobility changes are more affected by spatial parameters than non-spatial parameters. Therefore, county elevation data, the information on whether the county is located on the sea coast, and the latitude-longitude information of the county were used to investigate this situation specific to the province of Istanbul.

Elevation data is the first spatial variable predicted to affect community mobility change data. The province of Istanbul, with a surface area of 5,343 km², is a province where the altitude varies based on counties. For example, there is a difference of 318 meters between the lowest elevation value (Adalar county, 6m) and the highest elevation value (Maltepe county, 324m). In order to determine whether the change in community mobility is affected by this situation, the altitude values of the counties' centers were collected *(*İstanbul İlçeleri Haritası*, 2022)*.

Counties with a seacoast are assigned a value of 1, and counties that do not have a value of 0. This information was manually added to the data set by examining the Istanbul map.

Istanbul counties' latitude and longitude information was obtained from GitHub (NovaYear, 2019).

Non-spatial Variables

Non-spatial variables that affect mobility changes based on Istanbul counties will be discussed in this section.

The current number of shopping malls in the counties, population density (person/km2), the number of individuals with undergraduate and graduate degrees, and the ratio of elderly, young, and middle-aged individuals are obtained from the estimating real estate data analytics and insight platform Endeksa (*Endeksa*, 2017).

The monthly average household income data based on Istanbul counties, obtained from the report published by the Istanbul Governorship Open Door Branch Directorate (*Açık Kapı-İstanbul'un Sosyo Ekonomik Analizi*, 2021), was also added to the study as an independent variable. The purpose of adding the variable is to measure the contribution of monthly income amounts of individuals on a county basis to changes in community mobility. For example, in counties with high-income levels, individuals may have stopped going to their workplaces and chose to stay at home. However, individuals may have had to continue working in counties with low-income levels even if they were banned.

The number of illiterate individuals aged six and over on an Istanbul county basis was also obtained from the report published by the Istanbul Governorship Open Door Branch Directorate (*Açık Kapı-İstanbul'un Sosyo Ekonomik Analizi*, 2021) and added to the study as an independent variable. The purpose of adding the variable is to determine whether the education level of the individuals on a county basis affects compliance with the rules and measure its contribution to the community mobility changes.

Methodology

The first step was to create a dataset to identify the spatial and non-spatial factors influencing the COVID-19 based mobility changes in the counties of Istanbul. When choosing the features for the dataset, it was taken into account that the geographic characteristics of the counties and the demographic characteristics of their inhabitants could best explain the change in mobility at the specific places during the COVID-19 period. Then, to determine how well the spatial and sociodemographic features provided by the dataset explain the change in mobility, the variable selection method was applied in the second stage using the R package programming language. As a result, it was intended to quantify how independent variables affected changes in mobility.

The regression analysis determined the probability of producing the highest adjusted R2 value for non-spatial parameters. Then, the effect of spatial parameters on adjusted R2 value was measured for these values.

Due to the large number of spatial and non-spatial variables included in the study, it required a complex calculation to determine which variables affect the target variable and to find the differences between the effect levels of the influencing variables. The effects of 13 spatial and non-spatial variables on mobility changes under six different headings were investigated. The effect of 13 variables on six target variables will require many calculations considering different combinations. For this purpose, it was decided to use the “Best Subsets Regression Essentials” method of the R package programming language.

The study’s primary purpose is to calculate the extent to which spatial variables affect target variables. For this reason, when non-spatial variables affecting the target variable were included in the regression, the extent to which the four considered spatial variables affected the regression was investigated. In order to reveal this detail, the extent to which the obtained quality measures (Adjusted R2) changed when four spatial variables were included in the regression or not. In order to select the best model, the overall performances of the models were compared, and some statistical metrics and strategies were determined to select the best one. The estimation error of each model was measured, and it was decided to choose the one with the lower estimation error.

“Best Subsets Regression Essentials” is a method for choosing a model that uses best subsets regression to test every possible combination of the predictor variables and then chooses the best model based on some statistical criteria. This method is also known as “all possible models” and “all possible regressions.” The “leaps” library should be imported to use this methodology in the R package programming language environment.

A distinct least squares regression best subset should be constructed for each possible variable combination in order to carry out best subset selection. This means that all $\binom{p}{2} = p(p-1)/2$ models with exactly two variables should be fitted to all p models with exactly one variable. Now, the objective is to determine which of the resulting models is the best. The problem of choosing the best model from the 2^p options that are taken into account by best subset selection is not simple. Typically, there are two stages to this. The required statistics can be calculated with the help of the functions in the "leaps" library. These statistics are metrics such as Adjusted R2, Cp, and BIC. Using one of these criteria, the best model can be determined. For example, the Adjusted R2 criterion was used to determine the best model within the scope of the study. The adjusted R2 represents the proportion of variation in the outcome that is explained by the variation in predictors values. The higher the adjusted R2, the better the model. Algorithm 1 describes best subset selection methodology.

Algorithm 1 Best subset selection.

1: M_0 denotes the null model. M_0 contains no independent variables. This model makes a prediction about the sample mean for each observation.

2: For t = 1, 2, …p:

2.1: Fit all $\binom{p}{t}$ models that contain exactly t independent variables.

2.2: pick the best among these $\binom{p}{t}$ models (M_t). Here best is defined as having the largest Adjusted R2.

3: Select a single best model from among M_0, M_1, …, M_t using Adjusted R2.

Results and Discussion

The effect states and effect levels of the spatial and non-spatial parameters affecting the six dependent variables included in the study are different. The non-spatial parameters and the effects of these parameters on the regression specific to the dependent variables are given in Table 2. Expressions marked with X mean that the relevant independent variable affects the relevant dependent variable.

Table 2. *Non-spatial parameters and their effects on dependent variables.*

Parameter	GP	P	T	RR	R	W
NSV_1			X		X	X
NSV_2					X	
NSV_3		X	X	X		X
NSV_4				X		X
NSV_5	X	X	X	X	X	X
NSV_6	X				X	X
NSV_7	X		X	X		X
NSV_8	X					
NSV_9		X	X		X	X

Spatial parameters and the effects of these parameters specific to dependent variables on regression are given in Table 3.

Table 3. *Spatial parameters and their effects on dependent variables.*

Parameter	GP	P	T	RR	R	W
SV_1						
SV_2	X	X	X		X	
SV_3		X	X		X	
SV_4	X	X			X	X

In the following section, the information in the table is summarized on the basis of community mobility change parameters.

- *Spatial and non-spatial variables affecting the GP parameter*: The independent non-spatial variables affecting the community mobility change related to markets and pharmacies (GP) were determined as “number of undergraduate and graduate graduates,” “elderly population ratio,” “middle-aged population ratio,” and “young population ratio.” The independent spatial variables that positively affect the community mobility change related to markets and pharmacies (GP) were determined as “seaside” and “longitude.” Accordingly, the county is located by the sea, and the longitude value of the county center increases the mobility in the market and pharmacies. At the same time, the elevation and latitude variables decrease the visits to the market and pharmacies.
- *Spatial and non-spatial variables affecting the P parameter*: The independent non-spatial variables affecting community mobility change in parks (P) were determined as “number of shopping centers,” “average number of persons in the household,” and “number of undergraduate and graduate graduates.” Accordingly, the county’s household size, the number of shopping malls, and the number of undergraduate and graduate graduates affected the park visits. The independent spatial variables that positively affect the community mobility change in the parks were determined as “seaside,” “latitude,” and “longitude.” Accordingly, the fact that the county is located by the sea, while the latitude and longitude values of the county center increase the park visits, the elevation variable decreases the park visits.
- *Spatial and non-spatial variables affecting the T parameter*: The independent non-spatial variables affecting community mobility change in public transportation were determined as “average monthly income,” “number of shopping centers,” “number of undergraduate and graduate graduates,” “elderly population ratio,” and “population density.” Accordingly, the household income level, the number of shopping malls in the county, the county’s population density, the number of undergraduate-graduate graduates, and the middle-aged population ratio affected mobility in public

transportation. The independent spatial variables that positively affect the community mobility change in public transportation were determined as "latitude" and "longitude." Accordingly, while the latitude and longitude values of the county center increased the mobility in public transportation, the elevation and seaside variables decreased the mobility in public transportation.

- *Spatial and non-spatial variables affecting the RR parameter*: The independent non-spatial variables that affect the retail and recreation community mobility change were determined as "number of shopping centers," "average number of persons in the household," "number of undergraduate and graduate graduates," and "middle-aged population ratio." Accordingly, the number of shopping malls, household size, number of undergraduate-graduate graduates, and middle-aged population ratio affected retail and recreation mobility in the county. The independent spatial variable that positively affects the mobility of the retail and recreation community could not be determined.
- *Spatial and non-spatial variables affecting the R parameter*: The independent non-spatial variables affecting the residential community mobility change were determined as "average monthly income," "number of illiterate people," "number of undergraduate and graduate graduates," "elderly population ratio," and "population density." Accordingly, the average household income level, the number of illiterate people, the number of undergraduates and graduates, the proportion of the elderly population, and population density affected residential mobility. The independent spatial variables that positively affect the residential community mobility change were determined as "seaside," "latitude," and "longitude." Accordingly, the latitude and longitude values of the county center and the fact that the county is located by the sea increase the duration of staying at home, while the altitude variable decreases the duration of staying at home.
- *Spatial and non-spatial variables affecting the W parameter*: The independent non-spatial variables affecting workplace visits are "average monthly income," "number of shopping centers," "average number of persons in the household," "number of undergraduate and graduate graduates," "middle-aged population ratio," and "population density." Accordingly, the average household income level, the number of shopping malls in the county, the household size, the number of people with undergraduate and graduate degrees, the ratio of the middle-aged population, and population density affected workplace visits. The independent spatial variable that positively affects workplace visits has been determined as "longitude." Accordingly, while the longitude value of the county center increased the workplace visits, the variables of altitude, seaside, and latitude decreased the workplace visits.

Table 4 shows how much different combinations of non-spatial variables affect the adjusted R2 parameter in the regression model in which all spatial variables are included.

Table 4. *Change in Adjusted R2 according to different combinations of non-spatial variables.*

Parameter	Combination	Adjusted R2
GP	Add Seaside	Increases from 0.1531 to 0.1586
	Remove Elevation	Increases from 0,1378 to 0.1586
	Remove Latitude	Increases from 0.1325 to 0.1586
	Add Longitude	Increases from 0.1077 to 0.1586
	Remove Elevation & Add Seaside	Increases from 0.1316 to 0.1586
	Remove Latitude & Add Seaside	Increases from 0.1280 to 0.1586
	Add Longitude & Add Seaside	Increases from 0.1190 to 0.1586
	Remove Elevation & Remove Latitude	Increases from 0.1106 to 0.1586
	Add Longitude & Add Seaside & Remove Elevation	Increases from 0.1081 to 0.1586
	Add Seaside & Remove Elevation & Remove Latitude	Increases from 0.1053 to 0.1586
	Add Longitude & Remove Elevation	Increases from 0.0996 to 0.1586
P	Remove Elevation	Increases from 0.5096 to 0.5240
	Add Seaside	Increases from 0.4798 to 0.5240
	Add Longitude	Increases from 0.4385 to 0.5240
	Add Seaside & Remove Elevation	Increases from 0.4697 to 0.5240
	Add Seaside & Add Longitude	Increases from 0.4176 to 0.5240
	Add Seaside & Add Latitude	Increases from 0.3739 to 0.5240
	Add Latitude & Add Longitude	Increases from 0.3612 to 0.5240
	Add Seaside & Add Latitude & Add Longitude	Increases from 0.3501 to 0.5240
T	Remove Elevation	Increases from 0.7044 to 0.7065
	Remove Seaside	Increases from 0.6980 to 0.7065
	Add Longitude	Increases from 0.6612 to 0.7065
	Remove Elevation & Add Longitude	Increases from 0.6524 to 0.7065
	Add Latitude & Add Longitude	Increases from 0.5956 to 0.7065
RR	Remove Elevation	Increases from 0.3213 to 0.3358
	Remove Seaside	Increases from 0.3160 to 0.3358
	Remove Latitude	Increases from 0.3189 to 0.3358
	Remove Longitude	Increases from 0.3187 to 0.3358
	Remove Elevation & Remove Longitude	Increases from 0.3060 to 0.3358
	Remove Elevation & Remove Latitude	Increases from 0.3039 to 0.3358
	Remove Latitude & Remove Longitude	Increases from 0.3024 to 0.3358
	Remove Seaside & Remove Elevation	Increases from 0.3002 to 0.3358
	Remove Seaside & Remove Longitude	Increases from 0.2984 to 0.3358
	Remove Seaside & Remove Latitude	Increases from 0.2981 to 0.3358
	Remove Evl. & Remove Latitude & Remove Longitude	Increases from 0.2906 to 0.3358
R	Add Seaside	Increases from 0.7914 to 0.8039
	Add Longitude	Increases from 0.7755 to 0.8039
	Add Seaside & Remove Elevation	Increases from 0.7922 to 0.8039
	Remove Elevation & Add Longitude	Increases from 0.7851 to 0.8039
	Add Seaside & Add Longitude	Increases from 0.7746 to 0.8039
	Remove Elevation & Add Seaside & Add Longitude	Increases from 0.7805 to 0.8039
	Add Seaside & Add Latitude & Add Longitude	Increases from 0.6787 to 0.8039
W	Add Longitude	Increases from 0.8220 to 0.8498
	Remove Latitude & Add Longitude	Increases from 0.8195 to 0.8498
	Add Longitude & Remove Seaside	Increases from 0.8166 to 0.8498
	Add Longitude & Remove Elevation	Increases from 0.8161 to 0.8498

Limitations

Seasonality in the data can be misleading, as a baseline needs to be provided for analyzing activity in park visits. The report may be more valid when working with data covering other mobility activities less affected by seasonality.

GCMR does not provide mobility for those who are not mobile or whose location services are disabled. Therefore, the data shared by Google only represents some smartphone users or the entire population in Istanbul.

Conclusion

This study examined spatial and non-spatial independent variables affecting community mobility change parameters in 6 different domains presented by Google. Afterward, the impact rates and directions of the independent spatial variables on the regression were analyzed.

The results showed that the non-spatial independent variable "average monthly income" impacted mobility in public transportation, the duration of stay at home, and the amount of time spent at the workplace. The duration of stay at home was the only factor impacted by the non-spatial independent variable "number of illiterate people." The "number of shopping centers" non-spatial argument impacted mobility in parks, public transportation, retail, and recreation. The non-spatial independent variable "average number of persons in the household" impacted workplace length of stay and mobility in retail and recreation. The non-spatial independent variable "number of undergraduate and graduate graduates" impacted all six areas' mobility changes. The mobility in markets and pharmacies, the amount of time spent at home, and the amount of time spent at work were all impacted by the non-spatial independent variable known as the "elderly population ratio." The non-spatial "middle-aged population ratio" independent variable affected mobility in markets and pharmacies, public transportation, retail and recreation, and length of stay at workplaces. The non-spatial "young population ratio" independent variable only affected the mobility in markets and pharmacies. Finally, the non-spatial "population density" argument affected mobility at park visits, public transport, length of stay at home, and length at work.

According to the findings, the spatial "elevation" independent variable did not affect the mobility in any area positively or negatively. The spatial "seaside" independent variable positively affected mobility in markets and pharmacies, park visits, mobility in public transport, and duration of stay at home, and negatively affected activity in retail and recreation and duration of stay at work. The spatial variable of latitude positively affected park visits, mobility in public transport, length of stay at home, and negatively affected activity in grocery stores and pharmacies, retail and recreation, and length of stay at workplaces. The spatial "longitude" independent variable positively affected mobility in markets and pharmacies, park visits, stay at home and stay at workplaces, and negatively affected mobility in public transportation and mobility in retail and recreation.

Table 5 indicates the directions and impact rates of independent spatial variables' effects on changes in mobility.

According to the findings obtained from the table, the independent spatial variable that most positively affects mobility in markets and pharmacies and duration of stay at the workplace is "longitude." The independent spatial variable that most positively affects park visits, mobility in public transport, and length of stay at home is "latitude." A spatial variable that positively affects mobility in retail and recreation was not found. The independent variable that was affected the most negatively was found to be "seaside."

Table 5. *The directions and impact rates (SV: spatial variable, D: direction, N: negative, P: positive).*

GMP	**GP**		**P**		**T**		**RR**		**R**		**W**	
SV	Rate	D	Rate	D	Rate	D	Rate	D	Rate	D	Rate	D
SV_1	14.91874	**N**	2.818391	**N**	0.288948	**N**	4.520502	**N**	0.108913	**N**	0.726555	**N**
SV_2	3.579245	**P**	9.202555	**P**	1.210322	**N**	**6.266106**	**N**	1.582957	**P**	0.65951	**N**
SV_3	19.75203	**N**	**28.32589**	**P**	**11.01983**	**P**	5.291971	**N**	**13.36279**	**P**	0.31097	**N**
SV_4	**47.25765**	**P**	19.48304	**P**	6.843956	**P**	5.373901	**N**	3.665533	**P**	**3.38267**	**P**

Ethics Committee Approval: Ethical approval is not applicable, because this article does not contain any data with human or animal subjects.

Peer-review: Externally peer-reviewed.

Author Contributions: Conception/Design of Study- A.O.A., G.Ç.Ç.; Data Acquisition- A.O.A., G.Ç.Ç.; Data Analysis/Interpretation- A.O.A., G.Ç.Ç.; Drafting Manuscript- A.O.A., G.Ç.Ç.; Critical Revision of Manuscript- A.O.A., G.Ç.Ç.; Final Approval and Accountability- A.O.A., G.Ç.Ç.;

Conflict of Interest: The authors have no conflict of interest to declare.

Grant Support: The authors declared that this study has received no financial support.

References

Açık Kapı-İstanbul'un Sosyo Ekonomik Analizi. (2021). http://www.istanbul.gov.tr/acik-kapiistanbulun-sosyo-ekonomik-analizi

Aloi, A., Alonso, B., Benavente, J., Cordera, R., Echániz, E., González, F., Ladisa, C., Lezama-Romanelli, R., López-Parra, Á., Mazzei, V., Perrucci, L., Prieto-Quintana, D., Rodríguez, A., & Sañudo, R. (2020). Effects of the COVID-19 Lockdown on Urban Mobility: Empirical Evidence from the City of Santander (Spain). *Sustainability*, *12*(9), Article 9. https://doi.org/10.3390/su12093870

Beria, P., & Lunkar, V. (2021). Presence and mobility of the population during the first wave of Covid-19 outbreak and lockdown in Italy. *Sustainable Cities and Society*, *65*, 102616. https://doi.org/10.1016/J.SCS.2020.102616

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., Schmidt, A. L., Valensise, C. M., Scala, A., Quattrociocchi, W., & Pammolli, F. (2020). Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the National Academy of Sciences*, *117*(27), 15530–15535. https://doi.org/10.1073/pnas.2007658117

Chan, J. (2020). The geography of social distancing in Canada: Evidence from facebook. *Canadian Public Policy*, *46*(1), S19–S28. https://doi.org/10.3138/

Chang, M.-C., Kahn, R., Li, Y.-A., Lee, C.-S., Buckee, C. O., & Chang, H.-H. (2020). Variation in human mobility and its impact on the risk of future COVID-19 outbreaks in Taiwan. *MedRxiv*, 2020.04.07.20053439. https://doi.org/10.1101/2020.04.07.20053439

datastd-dev. (2022). *Spatial Regression*. GitHub. https://github.com/datastd-dev/SpatialRegression

Google. (2020). *COVID-19 Community Mobility Report*. https://www.google.com/covid19/mobility?hl=tr

Endeksa. (2017). https://www.endeksa.com/tr/

İstanbul İlçeleri Haritası. (2022). https://www.haritatr.com/istanbul-ilceleri-s22

Orro, A., Novales, M., Monteagudo, Á., Pérez-López, J. B., & Bugarín, M. R. (2020). Impact on City Bus Transit Services of the COVID–19 Lockdown and Return to the New Normal: The Case of A Coruña (Spain). *Sustainability 2020, Vol. 12, Page 7206*, *12*(17), 7206. https://doi.org/10.3390/SU12177206

Rice, W. L., & Pan, B. (2021). Understanding changes in park visitation during the COVID-19 pandemic: A spatial application of big data. *Wellbeing, Space and Society*, *2*, 100037. https://doi.org/10.1016/J.WSS.2021.100037

Saha, J., Barman, B., & Chouhan, P. (2020). Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 Community Mobility Reports, 2020. *Children and Youth Services Review*, *116*, 105160. https://doi.org/10.1016/J.CHILDYOUTH.2020.105160

Sulyok, M., & Walker, M. (2020). Community movement and covid-19: A global study using google's community mobility reports. *Epidemiology and Infection* https://doi.org/10.1017/S0950268820002757

NovaYear. (2019). *Türkiye İl-İlçe Enlem ve Boylam Koordinatları*. GitHub. https://gist.github.com/NovaYear/4fe0fd530aca8b0e0bc0992b356fa32a

Vitiello, A., Ferrara, F., Auti, A. M., Di Domenico, M., & Boccellino, M. (2022). Advances in the Omicron variant development. *Journal of Internal Medicine*, *292*(1), 81–90. https://doi.org/10.1111/joim.13478

Wen, L., Sheng, M., & Sharp, B. (2022). The impact of COVID-19 on changes in community mobility and variation in transport modes. *New Zealand Economic Papers*, *56*(1), 98–105. https://doi.org/10.1080/00779954.2020.1870536

WHO. (2020). *Coronavirus Disease (COVID-19) — Events as they happen*. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen

WHO. (2022a). *Coronavirus (COVID-19) Dashboard*. https://covid19.who.int

WHO. (2022b). *Türkiye—WHO Coronavirus Disease (COVID-19) Dashboard With Vaccination Data*. https://covid19.who.int

Wielechowski, M., Czech, K., & Grzęda, Ł. (2020). Decline in Mobility: Public Transport in Poland in the time of the COVID-19 Pandemic. *Economies 2020, Vol. 8, Page 78*, *8*(4), 78. https://doi.org/10.3390/ECONOMIES8040078

Supplementary: Istanbul districts

name	seaside	rakim_metre	enlem	boylam	rere	grophar	parks	transit	work	resi	income_m	oyb_2020	avm_sayisi	pop_dens (kisi/km²)	hane_2022	yfm_20228l, yl,dr)	yasli_orani	genc_orani	ortaYas_orani
Fatih	1	29	41,0166667	28,9333333	-31,1202	-7,8046	-10,5792	16,5327	-21,4768	6,8907	9714	7101	1	24187	3,04	59627	16	31	53
Zeytinburnu	1	24	40,990635	28,89614	-24,7555	21,9448	-16,0055	7,5473	-15,2117	6,2617	6703	4576	2	23638	3,72	32967	10	38	51
Güngören	0	45	41,0166667	28,8833333	-18,8974	16,3428	28,3451	14,0693	-18,4372	6,6685	6232	4395	1	40042	3,42	41836	13	35	52
Bakırköy	1	21	40,968155	28,8228	-35,918	13,9183	-18,6011	5,9621	-31,0988	8,0785	16269	1390	8	7540	2,99	75719	21	27	52
Bahçelievler	0	68	40,9975	28,8505556	-33,8825	10,4852	3,3114	20,5874	-25,1585	7,5423	8597	9268	3	34845	3,46	99363	11	35	54
Bağcılar	0	92	41,0455556	28,8405556	-22,082	-7,8537	2,2076	36,295	-18,1038	6,4836	5881	13562	3	17552	3,94	69904	8	41	51
Bayrampaşa	0	69	41,0481503	28,9004553	-30,2049	20,9448	-20,0055	4,7034	-19,612	6,2024	6401	3310	1	26995	3,4	39114	13	34	54
Esenler	0	127	41,0794133	28,8538545	-33,7787	9,4031	6,5409	20,4503	-19,8511	6,0983	5237	8768	0	40570	3,81	38584	8	41	51
Küçükçekmece	1	10	41,008658	28,775342	-14,9617	17,5845	-7,8579	20,892	-19,1544	7,3306	6561	12380	2	20779	3,43	123539	10	37	53
Avcılar	1	9	41,0153479	28,7314618	-19,5369	26,8684	17,3838	11,7076	-20,5615	7,4672	6736	5869	1	11497	3,4	66008	11	36	53
Beylikdüzü	1	109	40,9910381	28,6498144	-20,6995	30,5983	17,2482	10,5396	-20,2746	8,58	7959	2682	2	9620	3,35	78912	11	36	53
Esenyurt	0	55	41,0342806	28,6801194	-23,8456	72,3705	9,7513	23,1789	-11,0355	7,1939	5562	14834	4	22265	3,55	91613	6	43	52
Beyoğlu	1	58	41,0382864	28,9703304	-39,8798	-8,9439	-30,612	-19,0386	-20,0847	7,1936	8779	5069	2	25155	3,08	32417	12	33	55
Eyüp	1	71	41,1871598	28,8829816	-33,5451	6,6563	-16,1339	14,9131	-21,8839	8,3975	8590	5641	4	1591	3,28	70538	11	35	54
Gaziosmanpaşa	0	104	41,0759477	28,9004553	-13,1694	32,3069	18,4276	23,362	-21,1803	7,1885	5553	8768	1	40648	3,57	56793	11	38	52
Sultangazi	1	84	41,1255794	28,8713314	-12,1434	-0,8232	12,6776	41,4922	-14,9426	6,7377	4023	11177	0	14930	4,08	38979	7	43	50
Kağıthane	0	42	41,071	28,97	-26,8142	3,0141	11,4153	23,6104	-26,015	8,433	7703	6734	2	29494	3,26	70086	9	35	56
Şişli	0	99	41,06	28,987	-45,2527	-10,8373	-30,3607	-10,6872	-27,4781	9,0372	14388	3692	8	24253	2,64	72257	16	26	58
Beşiktaş	1	21	41,068616	29,0285355	44,9126	23,6407	-12,2787	-19,7322	-36,7654	9,9332	19424	950	2	9290	2,51	76761	22	23	55
Başakşehir	0	110	41,077895	28,812551	-27,4577	36,0254	0,1898	12,403	-14,9563	8,4795	8301	5155	4	4895	3,77	78063	6	44	50
Büyükçekmece	1	8	41,034133	28,590003	-18,8115	24,7835	25,7553	5,1889	-19,1926	7,5939	6752	2812	1	1851	3,29	45019	13	35	52
Sarıyer	1	59	41,166328	29,04995	-32,0806	-2,1042	-11,8634	2,9836	-30,179	9,6188	13442	4573	3	2265	3,09	81717	14	31	55
Arnavutköy	1	163	41,2	28,733333	-10,3479	43,8968	-32,9959	41,1527	-4,2103	7,8002	3734	6291	1	685	4,06	20569	7	46	48
Silivri	1	14	41,080158	28,26829	-11,3593	6,66	61,5049	54,4257	-5,3264	8,065	4363	2189	1	240354	3,56	26530	13	32	55
Çatalca	1	105	41,148239	28,46773	-3,7393	-31,6987	34,0056	31,8009	-9,5176	5,2048	3914	876	0	64081	2,82	9406	18	31	51
Kadıköy	1	60	40,980141	29,08227	-40,2295	-13,6995	-27,9112	-4,101	-33,7063	10,6068	16601	2711	2	19279	2,47	209465	26	21	53
Adalar	1	6	40,8763772	29,095444	0	-32,8378	54,2476	0	-8,2649	0	12236	206	0	1457	2,55	3860	27	23	50
Üsküdar	1	30	41,032236	29,031938	-36,3019	20,5028	-17,3251	12,2062	-29,2322	8,9754	12852	6755	3	14879	3,09	142141	16	31	54
Ataşehir	0	110	40,9833333	29,1166667	-35,1762	3,3239	-8,9672	12,0587	-25,5984	9,7117	12098	6684	7	16903	3,15	102141	12	33	55
Ümraniye	0	152	41,0303	29,1065	-30,2309	-1,6985	-13,6831	15,7322	-20,1571	8,5204	6690	10382	6	15862	3,41	134935	9	36	55
Sancaktepe	0	184	41,0287028	29,2901829	-16,056	43,6322	11,4303	22,1947	-14,7131	8,4644	4843	8083	1	7368	3,69	53667	6	42	52
Maltepe	1	324	40,949047	29,174109	-37,862	73,3889	-5,5901	6,9494	-26,7213	9,6174	10617	6543	4	9717	3,06	131449	15	30	55
Beykoz	1	124	41,132719	29,10569	-18,2525	22,6449	-1,7814	8,7553	-26,0806	8,3196	6793	4466	0	750	3,3	43338	15	33	53
Çekmeköy	0	16	41,104235	29,3177272	-16,5516	42,1046	4,5186	28,9009	-16,5342	8,7252	6443	3527	0	2105	3,42	48764	8	38	54
Sultanbeyli	0	135	40,9611123	29,2669438	-16,2008	16,4449	18,2062	24,2885	-7,3524	6,6949	3995	7705	2	11838	4,17	24389	6	46	48
Kartal	1	65	40,899651	29,193649	-30,1844	63,734	-5,5969	7,9494	-23,7678	8,5874	7578	7372	3	11862	3,16	101877	13	32	55
Pendik	1	39	40,879326	29,258135	-25,8661	37,8718	-22,2855	11,2691	-19,5109	7,5683	5619	10726	5	4058	3,42	115130	9	38	53
Tuzla	1	108	40,842	29,295	-14,4945	0,5014	-7,9248	11,6452	-13,4631	7,7264	6267	3045	1	2171	3,33	51207	8	38	54
Şile	1	29	41,1763889	29,6127778	20,1286	43,265	-29,9898	56,5628	6,6562	4,1602	4565	609	0	48	2,66	5493	25	27	48