REUE | Original Article

Relationship between population mobility, waves of COVID-19 cases, and hospital admissions for the disease: an analysis using the Google Mobility Index

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BACKGROUND AND OBJECTIVE. The COVID-19 pandemic obliged public health authorities to restrict population mobility in ways that had never before been done in Spain. The restrictions aimed to reduce pressure on the public health system. This study aimed to analyze population mobility in the Spanish autonomous community of Asturias to detect a possible impact on waves of the pandemic.

MATERIAL AND METHODS. Descriptive statistics were compiled and multivariate analysis was performed with 6 independent mobility variables, namely travel to shops and places of leisure, residential areas, parks, workplaces, supermarkets and pharmacies, and transportation hubs. Data for these variables were provided by the Google Mobility Index. We explored their relationships to 3 dependent variables, as follows: daily case counts, daily hospital admissions, and daily intensive care unit admissions. These statistics were provided by the Health Observatory of the Principality of Asturias. The period studied was from March 1 to December 31, 2020.

RESULTS. Population mobility decreased nearly 100% during the first and second waves. When restrictions were relaxed in the summer, displacement to open air spaces, such as parks, increased by 333%. Nine linear regression models detected significant associations between 5 of the 6 mobility variables (R^2 = 0.6) and variables reflecting the waves of infection. The 5 variables, depending on the type of mobility involved, predicted increases or decreases in daily cases or admissions for COVID-19.

CONCLUSIONS. The restrictions were widely followed by the population. Mobility indexes can be used to predict hospital admissions. We observed that although displacement toward parks and workplaces does not increase hospitalization rates, increased use of means of transport does have an impact on hospitalizations.

Keywords: Pandemics. Coronavirus. Health resource management Population mobility.

Análisis de la relación de la movilidad poblacional con la onda epidémica e ingresos por COVID-19 utilizando el Google Mobility Index

INTRODUCCIÓN. La pandemia por COVID-19 obligó a las autoridades de Salud Pública a tomar medidas de restricción de la movilidad de la población sin precedentes en España. Estas medidas tenían el objetivo de disminuir la presión sobre el sistema sanitario. El objetivo de este estudio es analizar la movilidad poblacional y su posible relación con la onda epidémica en Asturias.

MATERIAL Y MÉTODOS. Se realizó un estudio estadístico descriptivo y un análisis multivariante utilizando seis variables independientes de movilidad: tiendas y ocio, zonas residenciales, parques, lugares de trabajo, supermercados y farmacias y estaciones de transporte. Estos datos se obtuvieron por Google Mobility Index y fueron relacionados con tres variables dependientes sobre la onda epidémica en Asturias proporcionadas por el Observatorio de Salud del Principado de Asturias: casos diarios, ingresos diarios en hospitalización e ingresos diarios en unidad de cuidados intensivos (UCI). El periodo de estudio fue desde el 1 de marzo al 31 de diciembre de 2020.

RESULTADOS. La movilidad poblacional disminuyó hasta casi un 100% durante la primera y la segunda ola pandémica. Cuando se redujeron las restricciones en verano, la movilidad en espacios al aire libre, como los parques, aumentó un 333%. Se utilizaron 9 modelos de regresión lineal donde se obtuvieron resultados significativos en 5 de las 6 variables de movilidad con un R^2 = 0,6, con respecto a las variables de la onda epidémica, donde se predice un aumento o disminución de los casos diarios y/o los ingresos por COVID-19 dependiendo de la movilidad.

CONCLUSIONES. Las medidas adoptadas fueron seguidas mayoritariamente por la población, y los índices de movilidad pueden servir para establecer predicciones sobre los ingresos hospitalarios. Hemos observado que el aumento de movilidad en parques y lugares de trabajo no produjo un aumento de los casos de hospitalización. Esto sí ocurrió con el aumento de movilidad en los medios de transporte.

Palabras clave: Pandemias. Coronavirus. Gestión en salud. Movilidad social.

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Article Information: Received: 25-2-2023. Accepted: 7-4-2024. *Online:* 11-4-2024.
Editor in Charge: Guillermo Burillo-Putze.

Introduction

The COVID-19 outbreak began in Wuhan, China, in 2010 and was declared a pandemic by the World Health Organization (WHO) on March 11, 2020. The disease caused by this virus is called Coronavirus Disease 2019, abbreviated as COVID-19.[1] Coronaviruses are viruses that cause the common cold or severe illnesses. Symptoms may appear within 2 to 14 days, including fatigue, muscle pain, sneezing, sore throat, dry cough, high fever, and respiratory problems, which can progress to more severe conditions such as pneumonia, acute respiratory distress syndrome, kidney failure, or death.[2] A person can become infected within 1.8 meters, and the virus can survive from two hours to several days. The most important preventive measure is hand hygiene.[3-6] There is a positive correlation between mortality and health care expenditure; therefore, in densely populated areas, the surge in patients led to a shortage of resources, increasing infection among health care personnel.[7] Medical care activities were limited to urgent or priority cases only. Research activity in clinical trials was also reduced almost entirely.[9] To reinforce information services about COVID-19 and to guide individuals with symptoms or close contacts, exclusive phone lines were established due to the overload of emergency numbers. On the other hand, since the beginning of the pandemic, nearly one-third of the world's population was subjected to severe mobility restrictions.[10] On March 17, 2020, the European Union closed its external borders.[11] Never before had a pandemic had such a universal impact; decision-making was a challenge, but thanks to technology, data were collected and actions to combat the pandemic began.[12-15] Non-pharmaceutical interventions were the main means of effectively controlling the pandemic, grouped into five categories: social distancing, movement restrictions, public health measures, social measures, and economic measures, as well as global lockdowns,[16] aimed at delaying the infection peak and preventing the overburdening of the health care system.[17-20] COVID-19 not only had a high fatality rate but also spread rapidly, prompting travel restrictions, border closures, and the shutdown of schools, workplaces, businesses, gatherings, and events.[4,9,11,21] The greatest decrease in personal mobility occurred during peak hours when people traveled to work or school, as well as during shopping trips. Changes were also observed in public transport usage, with an increase in private car travel. Moreover, it is important to note that densely populated urban areas experienced faster spread compared to rural zones, leading individuals with higher socioeconomic status to relocate to less populated areas.[22-24] In Spain, a state of emergency was declared on March 14th 2020, marking the so-called first wave. From March 15th to June 21st, a nationwide quarantine was imposed, with home confinement.[25] This wave ended in late June, entering a "plateau period," but a second wave emerged in July, lasting almost until the end of the year. During this second wave, by the end of October, the Autonomous Communities imposed their own restrictions. On October 23rd, perimeter lockdowns by municipalities began in Asturias.[26] After each lockdown, reductions were observed, confirming that restrictions were effective.[10,27]

Google released the Google Mobility Index (GMI), which records mobility rates by country and region in specific locations, using pre-pandemic mobility as a baseline.[16,20,22,28-30] Population mobility can serve as an indirect measure of social distancing and helps explain the relationship between mobility, epidemic waves, and government restrictions, providing insight into the initial spread and the delayed effects of restrictions.[20,30,31] It is an important tool for epidemic tracking and for assessing the effectiveness of control measures.[32]

The objective of this study was to analyze population mobility and its possible relationship with the COVID-19 epidemic wave in Asturias.

Material and methods

We conducted a descriptive statistical study with multivariate analysis to examine the relationship between mobility restrictions and the epidemic wave in Asturias. A multivariate analysis was performed using the six variables provided by the GMI (parks, workplaces, transit stations, retail and recreation, grocery and pharmacy, and residential areas) and was correlated with data from the Asturias Health Observatory (daily cases, daily hospital admissions, and intensive care unit –ICU– admissions) during the period between March and December 2020. Analyses were performed 14, 20, and 30 days after the onset of restrictions. Thus, for multivariate analysis, independent variables ranged from March 1, 2020, to December 1, 11, or 17, 2020; dependent variables ranged from March 15, 20, or 30, 2020, to December 1, 11, or 17, 2020, respectively. Statistical analysis was conducted using R Studio. The descriptive study included mean, median, standard deviation (SD), quartiles, maximum, and minimum. For the multivariate analysis, a linear regression model was applied to each variable within different time windows, with a significance threshold of $P < .05$, obtaining regression coefficients, t values, and P values.

Ethical approval was not required for this study, and ethical principles for research involving human subjects were respected.

Results

The highest number of daily cases during the study period occurred on November 6th, 2020 (807 cases), the highest number of hospital admissions on November 9th, 2020 (1,157 cases), and the peak ICU admissions on November 6th, 2020 (150 cases). It should be noted that during the first 13 days of the study, there were no recorded data on hospital or ICU admissions; therefore, a numerical value of zero was assigned.

Table 1 presents the days of highest and lowest mobility according to the different locations analyzed by the GMI.

Figure 1 shows the graphical representation of mobility variation and the dependent variables analyzed.

Using multivariate analysis with a 14-day lag between independent and dependent variables (Table 2), significant

Table 1. Increase and decrease in mobility across the different locations analyzed

	Lowest mobility (date)	Highest mobility (date)
Retail and recreation	–97% (10/04/2020)	+15% (10/8/2020)
Grocery and pharmacy	–95% (10/4/2020)	+39% (30/12/2020)
Parks	–88% (29/3/2020)	+333% (5/8/2020)
Transit stations	–85% (10/4/2020)	+8% (4/3/2020)
Workplaces	–88% (10/4/2020	+12% (23/8/2020)
Residential areas	–81,7% (10/4/2020)	+34,3% (8/8/2020)

results were found for "Daily cases" and "Transit stations" (R^2 = 0.4153); for "Hospital admissions," the variables "Retail and recreation" and "Transit stations" (R^2 = 0.4821); and for "ICU admissions," the variables "Retail and recreation" and "Transit stations" (R^2 = 0.5576).

In the analysis with a 20-day lag (Table 3), significant associations were found for "Daily cases" with the variables "Parks," "Workplaces," and "Transit stations" (R^2 = 0.4634); for "Hospital admissions," the variables "Parks" and "Transit stations" (R^2 = 0.53); and for "ICU admissions," the variables "Retail and recreation," "Parks," and "Transit stations" (R^2 = 0.6042).

In the analysis with a 30-day lag (Table 4), significant relationships were found for "Daily cases" with the variables "Parks," "Workplaces," and "Transit stations" (R^2 = 0.4634); for "Hospital admissions," the variables "Parks," "Transit stations," and "Grocery and pharmacy" (R^2 = 0.6201); and for "ICU admissions," the variables "Parks," "Workplaces," and "Transit stations" (R^2 = 0.6405).

Figure 1 illustrates the evolution of mobility throughout the two epidemic waves in the different areas analyzed by Google Mobility Trends and the trends in positive COVID-19 cases, hospital admissions, and ICU admissions.

Discussion

Mobility restrictions during the COVID-19 pandemic varied depending on health care pressure and cumulative incidence, both across Spain and within each Autonomous Community individually, although they did not prevent the health care system from having to increase its response capacity.[33] Quarantine and home isolation were measures implemented to curb the rise in cases and hospital admissions, as no specific medical treatment was available and vaccines had not yet been developed. According to the

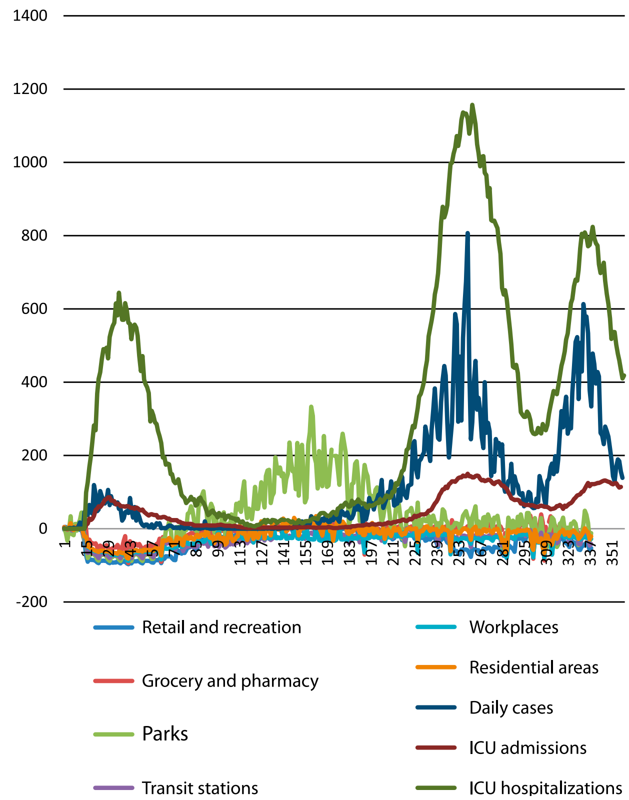

Figure 1. Percentage change in mobility from baseline and daily COVID-19 cases, hospitalizations, and intensive care unit (ICU) admissions.

mobility data provided by the GMI,[31] we were able to assess how population mobility evolved in Asturias during the pandemic and its relationship with epidemic waves. Previous literature has already linked mobility to various pandemic-related outcomes. For instance, high pre–COVID-19 mobility was associated with a later increase in mortality, using a 20-day quadratic regression model.[4] Other studies determined that a 10% decrease in mobility corresponded to a reduction of 0.04–0.07 in the effective reproduction number.[10]

In our study, two periods of high incidence were identified: the first between March and June (first wave), and the second between October and December (second wave). Differences between the two waves were evident, as daily cases and hospital admissions nearly doubled,

Table 2. Multivariate analysis with a 14-day lag

	Daily cases			Hospital admissions			ICU admissions		
	P-value	Multivariate regression coefficient	t (p)	*P*-value	Multivariate regression coefficient	t (p)	*P*-value	Multivariate regression coefficient	t (p)
Intercept		223.97149			480.5651			59.0806	
Retail and recreation	.137	–1.62863	–1.491	.00587*	–6.9232	–2.778	.000118*	–1.2025	–3.911
Parks	.231	–0.59665	–1.200	.14884	–1.6421	–1.448	.179260	–0.1885	–1.347
Workplaces	.344	–2.01287	–0.948	.21533	–6.0144	–1.242	.267617	–0.6638	–1.111
Transit stations	1.94e-06*	6.64235	4.873	6.07e-07*	15.9160	5.119	1.7e-07*	2.0637	5.379
Residential areas	.722	0.86758	0.357	.68396	2.2619	0.408	.643923	0.3170	0.463
Grocery and pharmacy	.923	–0.06024	–0.097	.81281	0.3375	0.237	.070208	0.3194	1.818

ICU: intensive care unit.

Table 3. Multivariate analysis with a 20-day lag

	Daily cases			Hospital admissions			ICU admissions		
	P-value	Multivariate regression coefficient	t (p)	*P*-value	Multivariate regression coefficient	t (p)	*P*-value	Multivariate regression coefficient	t (p)
Intercept		277.4671			687.879			87.44142	
Retail and recreation	.2250	1.2857	1.216	.1426	–3.544	–1.471	.00858*	–0.77895	–2.649
Parks	.0358*	–1.0094	–2.112	.0204*	–2.557	–2.333	.02679*	–0.29792	–2.228
Workplaces	.0155*	–4.9912	–2.437	.1506	–6.745	–1.442	.17199	–0.78177	–1.370
Transit stations	6.67e-08*	7.3200	5.574	8.09e-09*	17.950	5.971	1.1e-10*	2.47230	6.740
Residential areas	.5008	1.5754	0.674	.5763	3.000	0.560	.56353	0.37830	0.578
Grocery and pharmacy	.0639	–1.1869	–1.861	.2309	–1.657	–1.201	.84917	–0.03206	–0.190

ICU: intensive care unit.

reaching a peak of 807 daily cases, 1,157 hospital admissions, and 150 ICU admissions during November. These dates coincide with the period in which restrictions had to be tightened due to the health care pressure in Asturias, leading to perimeter lockdowns by municipalities. In contrast, during the summer, restrictions were eased, and cases dropped to zero — likely due to higher temperatures, unfavorable conditions for viral survival, and increased use of outdoor spaces for leisure activities.

Regarding mobility, almost all variables showed their lowest levels (near –100%) between March and June during home confinement, as expected, and increased mobility in summer during the so-called "new normality," characterized by less stringent restrictions and no home lockdown, although mask-wearing and social distancing were still enforced. During this period, population movement toward parks rose markedly, up to 333% higher than pre-pandemic levels, indicating that open-air areas were preferred for recreation. It is also worth noting that children, who had been unable to go outside since March, were finally allowed outdoors again, and parks provided safe environments where families could comply with safety measures. We observed that this large increase in outdoor mobility did not translate into a rise in cases in subsequent weeks. Therefore, in the event of future pandemics, outdoor environments could be established as safe zones.

Furthermore, holiday travel resumed, leading to increased mobility in residential areas and transit stations, with traffic exceeding levels seen in previous months. These patterns were repeated during the Christmas holidays. Workplaces also showed nearly pre-pandemic mobility levels during the summer, likely due to the reopening of shops, indoor restaurants, and hotels for tourism, as well as the reduction of remote work. An interesting observation from another variable was that the peak of mobility in transit stations occurred before confinement. This was probably because people wanted to return to their primary or secondary residences in anticipation of lockdowns, leaving large cities in advance.

In the multivariate linear regression analysis, significant results were found in all nine models for the variable "Transit stations", which was the only one predicting that an increase in mobility led to an increase in cases and hospital admissions — and vice versa. These are enclosed, crowded spaces with limited hygienic control, suggesting that in future pandemics, one of the first measures should be implementing restrictions on public transportation. Conversely, the other significant variables predicted a decrease in cases and/or hospitalizations with increased mobility. In the case of parks, as mentioned earlier, this may be due to people choosing open-air environments and maintaining adequate social distancing. The same applies to workplaces, where companies implemented strict hygiene and structural measures to protect workers and avoid infections that could lead to staff shortages. Thus, workplaces could be considered safe environments, provided that appropriate distancing and ventilation measures are maintained. As for the variables "Retail and recreation" and "Grocery and pharmacy," we found no reasonable explanation for the results obtained. It should also be noted that residential areas were not significant in any model, indicating that mobility in these locations did not influence case or hospitalization numbers — likely because the population remained largely at home or in nearby outdoor areas.

Table 4. Multivariate analysis with a 30-day lag

	Daily cases			Hospital admissions			ICU admissions		
	P-value	Multivariate regression coefficient	t (p)	*P*-value	Multivariate regression coefficient	t (p)	*P*-value	Multivariate regression coefficient	t (p)
Intercept		277.4671			887.5673			106.0041	
Retail and recreation	.2250	1.2857	1.216	.515855	1.4269	0.651	.35707	–0.2617	–0.923
Parks	.0358*	–1.0094	–2.112	.000456*	–3.5250	–3.554	.00207*	–0.3995	–3.115
Workplaces	.0155*	–4.9912	–2.437	.052915	–8.2640	–1.945	.04279*	–1.1190	–2.037
Transit stations	6.67e-08*	7.3200	5.574	3.74e-11*	18.8931	6.935	9.47e-13*	2.6576	7.543
Residential areas	.5008	1.5754	0.674	.417151	3.9397	0.813	.42898	0.4967	0.792
Grocery and pharmacy	.0639	–1.1869	–1.861	.006619*	–3.6236	–2.739	.24103	–0.2011	–1.175

ICU: intensive care unit.

According to the R^2 values, models with a 30-day lag between variables were more predictive for hospital and ICU admissions, although none achieved good predictive performance for daily cases or for models using 14- or 20-day intervals.

It is necessary to conduct similar studies to analyze the relationship between restriction measures, epidemic waves, and the health care burden on emergency services. Such research would help appropriately scale resources in advance.

Among the limitations, it is important to note that we used secondary data from Google, based on GPS-dependent information, which implies the presence of potential errors.

In conclusion, our study observed that the measures implemented were largely followed by the population and that mobility indices can serve as valuable variables, particularly for predicting hospital admissions. Increased mobility in parks and workplaces did not result in higher hospitalization rates, whereas increased mobility in public transport areas did correlate with a rise in hospitalizations.

ARTICLE INFORMATION

Conflict of Interest Disclosures: None reported.

Funding: The authors declare the non-existence of funding in relation to this article.

Ethical responsibilities: The authors have confirmed the maintenance of confidentiality and respect for the patient rights, agreement of publication, and transfer of rights to Revista Española de Urgencias y Emergencias.

Article not commissioned by the Editorial Board and with external peer review.

Note of the editors: This is a BOWMAN-generated English translation of the officially indexed Spanish-language article, which should be cited as Rev Esp Urg Emerg. 2024;3:84-89. In this translated version, the editors have supervised the process; however, it cannot be ruled out that some errors resulting from the artificial intelligence translation process may have gone unnoticed.

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