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SPATIAL IMPACT OF COVID-19 IN TURKEY

Understanding mobility dynamics using urban functions during the COVID-19 pandemic: comparison of pre-and post-new normal eras

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Abstract
Several changes in urban mobility patterns have been observed in response to COVID-19 since March 2020 when the World Health Organization (WHO) declared COVID-19 a pandemic. However, whether mobility changes are entirely pandemic related has not been investigated for each urban function. This paper evaluates the potential determinants of urban mobility changes for six different urban functions during the COVID-19 pandemic via community mobility data collected by Google. Using artificial neural networks (ANN), the dynamics that affect mobility changes in the following urban functions; grocery/pharmacy, residential, parks, retail/recreation, transport stations, and workplaces, were analysed for Çankaya, one of the densest districts in the capital of Turkey. Results of the prediction model show that responses to the pandemic differed considerably by urban function. Before the new normal era, changes in urban mobility trends were strongly dependent on the pandemic as a public health threat and represented by restrictive government measures. However, impacts of the pandemic on intracity mobility decreased in the new normal era when rules were relaxed. These results are useful for developing proactive policies to ensure rapid post-pandemic recovery in urban economics and planning.

Keywords Community mobility · COVID-19 · Urban functions · Artificial neural network

JEL classification C54 · E27 · R14

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1 Introduction

Mobility behaviours play a crucial role in the functioning of societies and affect urban life at many points; for instance, they cause social, economic, and cultural exchange, provide important indicators of everyday life practices, induce traffic congestion and pollution, and accelerate the spread of infectious diseases (Schläpfer et al. 2014). Human mobility behaviour is generally considered to be based on distance and time measurements; however, it can also be influenced by several external determinants, such as weather conditions, transport modes, and income status (Patla and Shumway-Cook 1999; Vilhemson 2005). Since being a goal-directed behaviour, mobility is recognized as an action based on individual choice. The means of transport used to hold the travels also vary according to the purpose. All these complexities have been the key motivator for scholars to investigate the dynamics of urban mobility patterns (Blommaert et al. 2017). As obtaining mobility data—especially from smartphones—became easier in the last decade, research at the urban and regional scale discussing issues related to transportation (Calabrese et al. 2013; Huang et al. 2018; Gao et al. 2019), economics (Dong et al. 2017), health (Arimura et al. 2020; Xu et al. 2021), and environment (Ford et al. 2016; Lu et al. 2016) have commonly seen.

Human mobility is among the most discussed topics in urban studies, as it reveals the relationship between people and space in the discourse on urban planning (Sun et al. 2011; Jahromi et al. 2016; Liu et al. 2021a, b). However, it is hard to understand the main reasons for mobility behaviours through basic analytical tools since the economic, social, historical, cultural, and political contexts of space are temporal (Saurin 2021). Analysing complex urban systems is key for drawing conclusions about spatial rearrangement since it reveals how patterns change when human movement loses momentum—as has happened almost throughout the world in the last two years.

The COVID-19 pandemic has cut into intracity mobility and required a rethinking of urban dynamics. Its greatest effect has been a major interruption of everyday life since many countries have imposed restrictions on community mobility to reduce disease transmission (Furceri et al. 2020). The pandemic became more than just a health crisis; it also posed a threat to the social and economic existence of cities and cultures (Cheshmehzangi 2021). Therefore, the changes in human mobility in different urban functions during the COVID-19 pandemic have attracted considerable attention from scholars. Previous research has identified mobility as a critical factor in explaining behavioural changes to manage the pandemic, and it has been discovered that different patterns of mobility can be found in different urban functions (de Oliveira et al. 2021). A study in Portugal, which examines the mobility patterns in different locations based on the number of cases, has revealed that the population quickly adopted the government measures, nonetheless, mobility, particularly in the parks, increased after the lockdown was over (Tamagusko and Ferreira 2020). A paper in the USA has found that community mobility at public transport stations decreased by 50%, followed by retail/recreation areas (45%) (DePhillipo et al. 2021). Mendolia et al. (2021) have

found that mobility in grocery/pharmacy and transport categories was similarly affected by COVID-19 cases, while mobility in workplace areas appeared to be less affected and mobility in parks was not affected. A study examining changes in mobility patterns for different location categories during the pandemic period in New York City has revealed that stay-at-home requirements reduced mobility at transit stations, while parks and recreation areas were slightly affected (Jiang et al. 2021). da Silva et al. (2021) have discovered that the first wave of pandemics caused a greater reduction in mobility, in addition to this, parks and grocery/pharmacy categories had opposite characteristics compared to the other ones in a study conducted in various parts of America and Europe. Li et al. (2021), examining changes in travel purposes during COVID-19, have revealed that the rates of resident, park, and grocery/pharmacy activities increased during the lockdown period, while the rates of leisure and shopping activities decreased. A paper by Y. Liu et al. (2021a, b) has discovered that the influence of COVID-19 on various urban functions was indicated over differing change patterns in different regions. A study in which effective reproduction number of COVID-19, weather conditions, and mobility trends were used as an indicator found that the decrease in mobility in retail/recreation and transport station areas was efficient in reducing the number of cases; whereas the increase in time spent in the parks prevented the spread of the pandemic (Ghirelli et al. 2022).

Despite considerable progress, there is currently insufficient research on the non-linear determinants of mobility change. Most papers, on the other hand, fully focus on the impact of the COVID-19 pandemic. However, the production shortage caused by the lockdowns, as well as the support offered to individuals suffering from income loss in Turkey, have lowered financial strength (Küçükoğlu 2021). On the other hand, although weather conditions are known to be a natural factor affecting mobility, a limited number of studies included weather conditions in their analysis (Ghirelli et al. 2022). Therefore, it should be acknowledged that mobility patterns may also have been delivered of economic and weather-wise factors, which implies that the scope of studies associated with mobility pattern change must be widened.

The purpose of this paper is to understand the determinants of pandemic-induced changes in intracity mobility in the following urban functions; grocery/pharmacy, parks, transit stations, retail/recreation, residential, and workplaces. One of our testable hypotheses is that the government measures to contain the spread of the COVID-19, such as travel restrictions, stay-at-home requirements, and school and workplace closures are not determinative of the mobility changes in every urban function. The other hypothesis is that the influence of the pandemic on mobility changes remains in the background after the post-NN era. Lastly, both economic factors—such as the depreciation of TRY or economic support to households—and weather conditions have an impact on urban mobility change, as well as the COVID-19 pandemic. To evaluate our hypotheses, we used distance correlation and stepwise sensitivity analysis methods, the details of which are described in the Materials and Methods section.

Compared to previous studies, this study contributes to the current international list of literature on this topic in three ways. First, the data we analysed are beyond being just pandemic-related, but the non-linear model also identifies the

weather-wise and economic determinants of change in the mobility pattern. Second, while analysing the impact of COVID-19 on different urban functions, we compare the pre-and post-periods described as the *new normal (NN)* by the Turkish authorities. Third, we used daily sequence data, meaning that we could monitor the change day by day.

2 Materials and methods

2.1 Study area and data collection

The COVID-19 epidemic was first reported at the end of 2019, and it was declared a global pandemic by the World Health Organization (WHO) on March 11, 2020 (Cucinotta and Vanelli 2020). The first death due to COVID-19 occurred in Turkey on March 15, 2020, making the COVID-19 pandemic a life-threatening incident in the country. During the global pandemic, the Turkish government responded fast and took immediate measures. The primary measures adopted include distance learning, restrictions on public gatherings such as sports contests and concerts, the closure of workplaces such as gyms, shopping malls, restaurants, and cafés, and eventually restrictions on internal and international travel (Balçık et al. 2021). All these restrictions affected the urban mobility of Ankara, the capital and second most populated city in Turkey, and changed the way urban space is used. Among all the districts of Ankara, Çankaya is a suitable place to monitor mobility change since it comprises public institutions and organizations, major commercial centres, and the most heavily used transit corridors (Satılmış et al. 2021). Therefore, Çankaya, located in the central part of Ankara (Fig. 1), was selected as study area to determine the changing dynamics of urban mobility by different location categories.

Çankaya is the largest district in Ankara in terms of population and area. Considering the population density, it ranks sixth among the districts of Ankara with 796 inhabitants per square kilometres. Representing the capital of Turkey, the district includes business centers, shopping malls, important historical sites, and the main decision-making bodies of Turkey. The high commuter-adjusted population makes the district dense and dynamic. The abundance of transportation alternatives and high-level transportation relations allow interaction with the rest of the city. A study examining accessibility levels through transport modes in Ankara evaluates that Çankaya is above all other districts in terms of type and quality (Önder and Akdemir 2021). Thus, it offers unlimited possibilities and dynamic spatiality in the everyday life of the inhabitants, which makes it functional for examining mobility change.

The variables depend on the mobility changes in six urban functions in Çankaya, Ankara, over 731 days between 15 March 2020 and 15 March 2022 are analysed, and two periods rendering *pre-and post-new normal eras,* which are also called *pre-NN* and *post-NN,* are compared. The new normal era started on 1 July 2021. The mobility patterns after the new normal era have a different structure than before, as can be seen in Fig. 2. Revealing this difference makes it easier to understand the reasons behind the behavioural change of individuals. Therefore, the impacts of multiple characteristics—such as the pandemic-induced government responses, economic



Fig. 1 Border of Ankara (**a**) and location of the study area (**b**)

support during the pandemic period, depreciation rate of Turkish Lira (TRY), the daily number of deceased, and weather—on mobility changes in Çankaya were estimated by artificial neural network (ANN) models. The data set also includes economic factors and weather variations in addition to pandemic-related data to find out whether the current economic climate and weather conditions influence daily trips.

Community mobility data collected and reported by Google LLC (2022) between 15 March 2020 and 15 March 2022 were used as response variables in the study. This data set indicates the change in visits to different urban functions in Çankaya compared to baseline. The five-week period between 3 January 2020 and 6 February 2020, which characterized the pre-pandemic days, is chosen as reference values represented by the median of the visits while calculating the change from baseline. Using smartphone-GPS data to understand human behaviour provides a chance to

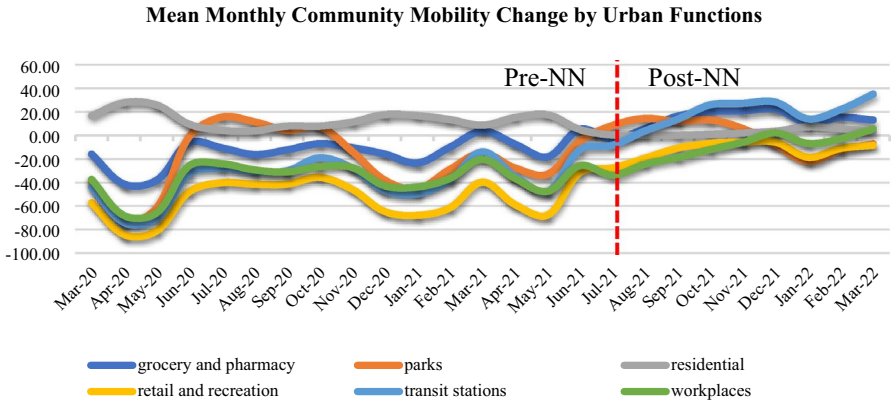


Fig. 2 Mean monthly community mobility change in Çankaya for different urban functions between March 2020 and 2022 (Google LLC 2022)

reveal the relationship between urban development and public health, as well as an essential source for analysing the spatial consequences of the pandemic crisis.

According to the data set, which can be seen in Table 1, grocery/pharmacy mobility change implies mobility trends related to grocery markets, pharmacies, drug stores, farmer markets and food stores; parks mobility change implies mobility trends for places such as national parks, local parks, public gardens and squares; transit stations mobility change shows the public transport hubs' mobility trend such as subways; retail and recreation category stands for cafés, restaurants, shopping centers and movie theatres; lastly, residential and workplace mobility change refers to the mobility trends regarding places of residential homes and office complexes.

*Where y represents response variables, x represents input variables

To assess the effects of weather conditions, the mean daily temperature (°C) was used as an independent variable. Due to missing data on daily COVID-19 cases in Turkey, the daily number of deaths caused by COVID-19 was included in the model as an independent variable. On the other hand, government measures containing interventions that limit the daily volume of trips are expected to be helpful for spatial implications. The face mask includes policies regarding the obligation to wear a mask. Restrictions on internal movements point to policies relating to restrictions on travels between cities/regions and/or intracity travels. School closing refers to government policies concerning the closure of schools and universities or providing distance learning, while workplace closing refers to government policies concerning workplace closure or working from home. Stay-at-home measures include requirements or recommendations to not leave the house. It should be noted that the measure changes from a recommendation to a requirement as the value of the data increases from one to three. The economic support index evaluates the economic response of governments, represented through income support and debt/contract relief of the household. The depreciation rate of TRY under the United States Dollar (USD) and the economic support index are expected to respond to the quest for a considerable socio-economic inference, especially after bending domestic mobility

Table 1 Details of the variables

Data	Data range*	Data source
Spatio-Temporal (Çankaya)		
Grocery/pharmacy mobility change (*GP*)	$-97 \le y \le 56$ (%)	Google LLC (Public Community Mobility Data)
Parks mobility change (*PA*)	$-95 \le y \le 44$ (%)	
Residential mobility change (*RS*)	$-6 \le y \le 46$ (%)	
Retail/recreation mobility change (*RT*)	$-99 \le y \le 6$ (%)	
Transit stations mobility change (*TS*)	$-94 \le y \le 52$ (%)	
Workplace mobility change (*WP*)	$-92 \le y \le 10$ (%)	
Weather (Ankara)		
Mean daily temperature (*DT*)	$-7 \le x \le 39$ (°C)	Turkish General Directorate of Meteorology
Medical (Turkey)		
Daily deaths of COVID-19 (*CD*)	$0 \le x \le 394$ (person)	Turkish Ministry of Health
Government Measures (Turkey)		
Face masks (*FM*)	0, 1, 2, or 3	The Oxford COVID-19 Government Response Tracker
Restrictions on internal movements (*IR*)	0, 1, or 2	
School closing (*SC*)	0, 1, 2, or 3	
Stay-at-home requirements (*SH*)	0, 1, 2, or 3	
Workplace closing (*WC*)	0, 1, 2, or 3	
Economic (Turkey)		
Depreciation rate of TRY (*DL*)	$-64.30 \le y \le 3.90$ (%)	Central Bank of the Republic of Turkey
Economic support index (*ES*)	$0 \le y \le 87.5$ (%)	The Oxford COVID-19 Government Response Tracker

restrictions that caused a production shortfall. The depreciation rate of TRY is calculated according to Eq. (1).

$$dR_{TRY} = \frac{Rt_1 - Rt_0}{Rt_0}.100 \tag{1}$$

where dR_{TRY} indicates the depreciation rate of TRY, Rt_1 is the rate obtained by dividing TRY by USD in t_1 time, and Rt_0 is a fixed rate that represents the average TRY-USD exchange rate of a five-week period between 3 January 2020 and 6 February 2020. This time frame coincides with the period of community mobility change calculations by Google LLC. Since the forex market is closed on weekends, the exchange rate on Friday is assumed to be valid on Saturday and Sunday as well.

2.2 Data analysis

Data analysis was carried out in two steps. In the first step, we investigated the interdependencies of the input variables and the response variable by performing correlation analysis. The distance correlation function (DC) and Pearson's correlation (PC) were employed together, and the results were compared to understand whether the relationship between the independent and response variables is non-linear. In the second stage, we endeavoured to reveal the relationship between mobility changes and input variables. We built twelve time series forecasting model using artificial neural networks (ANN) and attempted to explain the change in community mobility through weather, daily deaths of COVID-19, government measures, depreciation of TRY, and the economic support index. We also improved our analysis to compare pre-and post-new normal eras, during which government restrictions are reduced. Hence, this is the meaning of the phrases pre- or post- in the continuation of the research.

ANN is a machine learning technique that is based on modelling the learning process. It is a powerful tool that provides the modelling of complex relationships and allows for a more accurate prediction of determinants (Mohamady et al. 2014). The key benefit of ANN is its ability to learn the complex structure of any system. Urban is an open system that is affected by external factors as well as internal factors, and it is essential to use complex problem-solving tools, such as ANN, to examine this non-linear structure. The other benefit of ANN is its ability to learn about hidden relationships, which offers an advantage for estimating variational data such as mobility during the COVID-19 pandemic. Therefore, it is an effective algorithm for exploring complex and variational dynamics of community mobility that contributes to the development of an urban system that adapts to behavioural changes (Coulson et al. 2021).

During the modelling process, 80% of the data was used to train the model, 10% was used to validate, and 10% was used to test. Bayesian regularization was chosen as the ANN training algorithm because of its good generalization for noisy and small datasets (Negash and Yaw 2020). Looking at the structure of the ANN model, the hidden layer has five nodes, as calculated by Eq. (2). Where Y is the number of nodes in the hidden layer, and n is the number of input variables.

$$Y = Ceil(\frac{n+1}{2}) \tag{2}$$

According to the literature, the black box feature in the knowledge representation of the ANN is a limitation that makes the structure of the constructed model difficult to justify (Matel et al. 2019). Despite this challenge, which beclouds the examination of the relationships between dependent and independent variables, ANN can learn in the most realistic manner and so has the potential to improve the decision-making process on critical issues concerning urban space (Maithani et al. 2007; Jafar et al. 2010).

2.2.1 Distance correlation

We employed the distance correlation function (DC), which was recently introduced by Székely et al. (2007), to assess and test non-linear dependency between sets of random variables. Unlike Pearson's correlation, DC is a method for identifying both linear and non-linear relationships between variables, therefore better fits complex problems (Hou et al. 2022). The DC function, where input variable represents x_1 and response variable represents y, $dCor(x_1, y)$ is calculated using Eq. (3).

$$dCor(x_1, y) = \frac{dCov^2(x_1, y)}{\sqrt{dVar(x_1).dVar(y)}} \tag{3}$$

where $dCor(x_1, y)$ represents the DC between x_1 and y, $dVar(x_1)$ is distance variance of x_1, $dVar(y)$ is distance variance of y, and $dCov^2(x_1, y)$ is distance covariance of x_1 and y (Székely et al. 2007). When $dCor(x_1, y) = 0$, the relationship between sets of random variables is independent. In other words, $dCor(x_1, y)$ coefficient, which is a non-negative number, takes a value of zero if and only if the variables are independent (Edelmann et al. 2019). If $dCor(x_1, y) = 1$, then the variables have a very strong correlation.

2.2.2 Stepwise sensitivity analysis

We used stepwise sensitivity analysis to rank the importance of input variables. This method helps to evaluate which input variables are the most influential and effective and is also a simple way to open the black box. An input variable is omitted in the stepwise sensitivity method, then the error rate of the model is recorded. This procedure is repeated for all input variables step by step (Cao et al. 2016), which enables exploration of the model's response to uncertain input variables (Mohanty and Codell 2002). The sensitivity weights of the network to the presence of input variables (W_n) are calculated through Eq. (4).

$$W_1 = \frac{RMSE[ANN(x_2, x_3, \ldots, x_n), y]}{RMSE[ANN(x_1, x_2, \ldots, x_n), y]} \tag{4}$$

where W_1 is the sensitivity weight of x_1, and n is the number of input variables. If $W_1 > 1.00$, then x_1 is fit to the network; thus eliminating x_1 from the input variable

set will end up in a significant decrease in the error rate of the prediction model (Xu et al. 2021). Although identifying the impact of agents is not properly possible with this method, what affects a complex and unexplained system behaviour can be tested.

We evaluated the error rates using root mean square error (RMSE), calculated using Eq. (5). Where y_i is the response variable, $\hat{y}_i$ is the response of the network, and n is the length of the data.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

3 Results

3.1 Distance correlation coefficients

According to the scatter plots, the points show a non-linear trend for the most part, with no general pattern (Figs. 4 and 5 in Appendix A). As a result, applying Pearson's correlation (PC) to evaluate the presence of a relationship between input and response variables for a complex problem such as mobility change during the pandemic period could be ineffective, since PC merely identifies linear interactions. On the contrary, the distance correlation considers and captures both linear and non-linear relationships between X and Y, as previously stated. In this regard, we applied both DC and PC measures for comparison (Tables 2 and 3). Correlation coefficients of 0.5 to 0.7 and − 0.5 to − 0.7 are indicated by light grey cells, whereas coefficients greater than 0.7 and less than − 0.7 were indicated by dark grey cells.

The distance correlation vanishes if and only if X and Y are independent. The closer the correlation coefficient to one, though, the better the dependency is. When we applied DC to test our hypothesis on pandemic-dependent mobility change, we found that the coefficients were greater than zero for all independent

Table 2 DC and PC coefficient of variables in the pre-NN era

Variables	*GP*		*PA*		*RS*		*RT*		*TS*		*WP*	
	DC	*PC*	*DC*	*PC*	*DC*	*PC*	*DC*	*PC*	*DC*	*PC*	*DC*	*PC*
ES	0.27	0.06	0.43	0.39	0.36	-0.35	0.36	0.23	0.39	0.18	0.34	0.23
DL	0.23	-0.21	0.20	-0.17	0.24	0.21	0.27	-0.25	0.34	-0.33	0.27	-0.20
DT	0.18	0.00	0.49	0.44	0.41	-0.32	0.32	0.25	0.21	0.11	0.18	0.10
FM	0.33	0.27	0.49	0.47	0.55	-0.51	0.48	0.42	0.51	0.46	0.54	0.46
CD	0.17	-0.03	0.36	-0.29	0.37	0.32	0.33	-0.29	0.23	-0.15	0.22	-0.20
IR	0.22	-0.11	0.33	-0.35	0.31	0.36	0.32	-0.29	0.31	-0.22	0.33	-0.34
SC	0.31	-0.29	0.17	-0.12	0.24	0.23	0.25	-0.31	0.35	-0.40	0.24	-0.29
SH	0.20	-0.20	0.20	-0.22	0.22	0.23	0.23	-0.26	0.25	-0.27	0.25	-0.25
WC	0.20	-0.21	0.39	-0.40	0.44	0.46	0.35	-0.42	0.28	-0.35	0.35	-0.39

Table 3 DC and PC coefficient of variables in the post-NN era

Variables	*GP*		*PA*		*RS*		*RT*		*TS*		*WP*	
	DC	***PC***	***DC***	***PC***	***DC***	***PC***	***DC***	***PC***	***DC***	***PC***	***DC***	***PC***
ES	0.56	-0.53	0.42	0.35	0.42	-0.35	0.61	-0.56	0.77	-0.71	0.65	-0.62
DL	0.28	-0.21	0.68	0.63	0.75	-0.61	0.29	-0.26	0.57	-0.53	0.76	-0.66
DT	0.39	-0.26	0.70	0.67	0.74	-0.66	0.42	-0.28	0.63	-0.51	0.69	-0.59
FM	0.12	0.03	0.24	0.13	0.21	-0.09	0.14	-0.14	0.42	-0.36	0.41	-0.33
CD	0.44	0.46	0.19	-0.04	0.24	0.12	0.47	0.41	0.45	0.35	0.33	0.23
IR	0.48	0.35	0.21	-0.17	0.24	0.18	0.42	0.26	0.47	0.21	0.37	0.19
SC	0.28	-0.27	0.38	0.36	0.42	-0.40	0.20	-0.23	0.34	-0.31	0.41	-0.34
SH	0.49	-0.52	0.25	0.23	0.35	-0.29	0.54	-0.54	0.64	-0.64	0.51	-0.53
WC	0.50	0.36	0.25	-0.11	0.28	0.16	0.46	0.23	0.55	0.14	0.45	0.11

variables. This fact is a statistical measure of the dependence between variables. If, on the other hand, the connection between the independent and response variables is non-linear, PC converges to zero whereas DC does not (Huo and Székely 2016). The relation between grocery/pharmacy mobility change and economic support index, temperature, and deaths of COVID-19 variables in the pre-period can be examined to observe this pattern. Similarly, relationships between the change in mobility of public transport stations and workplace closure, or between workplace mobility change and restrictions on internal movements and workplace closure were discovered in the post-period that PC could not detect. For most of the cases in Tables 3 and 4, DC coefficients were relatively high, and PC coefficients were relatively low, meaning that it is appropriate to apply a non-linear regression model.

Table 4 Weights and RMSE values of input variables in the pre-NN era

Variable	*GP*		*PA*		*RS*		*RT*		*TS*		*WP*	
	RMSE	*W*	*RMSE*	*W*	*RMSE*	*W*	*RMSE*	*W*	*RMSE*	*W*	*RMSE*	*W*
All	22.19	1.00	20.40	1.00	4.85	1.00	12.75	1.00	14.38	1.00	11.99	1.00
ES	21.65	0.98	18.90	0.93	4.86	1.00	13.40	1.05	15.85	1.10	12.20	1.02
DL	23.45	1.06	19.12	0.94	4.63	0.95	11.50	0.90	13.98	0.97	11.50	0.96
DT	23.30	1.05	20.46	1.00	4.73	0.98	12.00	0.94	14.60	1.02	11.52	0.96
FM	24.38	1.10	20.45	1.00	4.48	0.92	13.14	1.03	15.00	1.04	12.87	1.07
CD	21.70	0.98	20.41	1.00	4.79	0.99	13.40	1.05	15.43	1.07	11.60	0.97
IR	23.30	1.05	19.00	0.93	4.73	0.98	11.50	0.90	16.29	1.13	12.43	1.04
SC	19.90	0.90	20.42	1.00	4.56	0.94	13.20	1.04	16.44	1.14	12.48	1.04
SH	22.10	0.99	20.47	1.00	4.90	1.01	12.90	1.01	14.49	1.01	12.40	1.03
WC	23.40	1.05	20.48	1.00	4.81	0.99	13.48	1.06	15.49	1.08	12.47	1.04

Table 5 Weights and RMSE values of input variables in the post-NN era

Variable	*GP*		*PA*		*RS*		*RT*		*TS*		*WP*	
	RMSE	*W*	*RMSE*	*W*	*RMSE*	*W*	*RMSE*	*W*	*RMSE*	*W*	*RMSE*	*W*
All	9.39	1.00	15.15	1.00	2.28	1.00	6.95	1.00	7.40	1.00	9.39	1.00
ES	7.80	0.83	13.15	0.87	2.18	0.96	6.00	0.86	8.00	1.08	8.00	0.85
DL	10.45	1.11	11.00	0.73	2.29	1.00	8.47	1.22	9.47	1.28	9.48	1.01
DT	10.54	1.12	16.30	1.08	2.59	1.14	8.35	1.20	8.30	1.12	10.40	1.11
FM	8.67	0.92	8.90	0.59	1.97	0.86	6.50	0.94	6.50	0.88	9.44	1.01
CD	8.73	0.93	11.16	0.74	2.30	1.01	6.50	0.94	8.00	1.08	8.78	0.94
IR	9.42	1.00	10.00	0.66	2.27	0.99	6.60	0.95	7.80	1.05	8.56	0.91
SC	9.33	0.99	14.69	0.97	2.27	0.99	6.58	0.95	7.90	1.07	8.66	0.92
SH	7.31	0.78	12.26	0.81	2.24	0.98	6.77	0.97	5.77	0.78	7.69	0.82
WC	8.51	0.91	9.90	0.65	2.22	0.98	6.50	0.94	7.50	1.01	9.40	1.00

Table 6 Ranking of the most influential input variables in the models for the pre-and post-NN eras

Variable		*GP*		*PA*		*RS*		*RT*		*TS*		*WP*	
		Pre-NN	*Post-NN*	*Pre-NN*	*Post-NN*	*Pre-NN*	*Post-NN*	*Pre-NN*	*Post-NN*	*Pre-NN*	*Post-NN*	*Pre-NN*	*Post-NN*
Economic	***ES***					2		3		3	3	6	
	DL	2	2				3		1		1		2
Weather-wise	***DT***	5	1	3	1		1		2	7	2		1
Pandemic	***FM***	1		4				5		6		1	3
	CD			6			2	2		5	4		
	IR	4	3							2	6	4	
	SC			5				4		1	5	2	
	SH			2		1		6		8		5	
	WC	3		1				1		4	7	3	4

3.2 Results of stepwise sensitivity analysis

Considering each of the six urban functions was examined for the pre-and post-NN eras, a total of twelve ANN models were established in the study, which required one hundred and twenty runs. Each model was subjected to stepwise sensitivity analysis to test the determinants of mobility change in each location category. Tables 4 and 5 show the independent variable weights calculated for the pre-and post-NN eras. The grey cells in Table 6 indicate that the weight of the independent variable in the model is greater than 1.00, which means that removing these variables from the relevant model does not decrease the error rate.

According to the SA results, the depreciation rate of TRY, temperature, wearing a face mask, restrictions on internal movements, and workplace closure were all the most significant factors in the pre-NN mobility change in grocery/pharmacy locations. Nonetheless, the depreciation rate of TRY, temperature—that were the top two influential ones—and restrictions on internal movements were the most determinative in the post-period.

Temperature, in addition to COVID-19-related factors, was identified as influential in the change in park areas' mobility; however, once government restrictions were relaxed, the mobility of the parks became dependent only on weather conditions.

The change in mobility of residential areas was best explained by the economic support index and stay-at-home requirements in the pre-NN era. On the other hand, with the NN era, residential mobility was found to be strongly influenced by temperature, the depreciation in TRY, and the number of deaths related to COVID-19. However, weather conditions were found to be the most influential on the mobility of residential areas in the post-NN era.

While government restrictions remained in effect, retail mobility was highly dependent on pandemic-related circumstances. Nonetheless, the depreciation rate of TRY was viewed as the most significant factor that influenced the retail mobility circumstances in the post-NN era, while weather conditions took second place.

Although nearly all factors have an influence on mobility in transit stations in the first period, the daily change was better explained by school closures, restrictions on internal movement, and the economic support index. The influence of stay-at-home requirements on the model was not found to be significant in the post-NN period, as the decision to restrict the number of passengers or seat capacity for intracity and intercity public transportation modes was abolished. On the other hand, the depreciation rate of TRY and the daily temperature were strongly influential in explaining the mobility change seen in transit stations.

Workplace mobility was determined to be strongly related to pandemic restrictions in the period up to 1 July 2021. In the post-NN period, on the other hand, all workplaces were reopened by the presidential decree. The four variables that were represented as weather, the depreciation rate of TRY, face masks, and workplace closure responded above the overall RMSE of the model.

4 Discussions on community mobility change in Çankaya by urban functions

The change in community mobility related to COVID-19 for six different urban functions was discussed in this case study conducted in Çankaya, which is the largest district in Ankara. The following results can be drawn from the findings of sensitivity analysis and distance correlation:

According to the findings of the ANN models, the closure of the workplace and stay-at-home requirements, which are thought to be successful in encouraging the community to have less contact with others, were the most influential variables determining mobility trends in Çankaya prior to the new normal era. However, during the NN era, the depreciation rate of TRY and the daily temperature had a strong impact on explaining mobility changes. This implication supports the hypothesis that the dominance of the pandemic on changes in mobility patterns may have become in the background with normalization.

Mobility trends in the grocery/pharmacy functions were found to be most affected by the face-covering measure before the NN era. Both grocery and pharmacy units

providing services for basic needs had the privilege of being open during the lockdown, even when the measure of face-covering was always required outside the residences. Panic buying (*hamsterkauf*) in the days of lockdown announcements may also have had an impact on mobility changes in the grocery and pharmacy areas. For these reasons, grocery/pharmacy visits were found not to be strictly correlated with pandemic-induced variables in both periods. In fact, a study conducted in Turkey shows that increased mobility in grocery/pharmacy reduces the number of COVID-19 patients (Akogul and Filiz 2021).

As an indirect effect of the reduction in the number of patients resulting from the use of the mask, it is observed that the face-covering regulation has influenced the mobility trend towards all non-residential functions as well, in the pre-NN era. The measure of wearing masks in closed public areas or places where social distance cannot be maintained also remained in the NN era. The fact that the Central Business District (CBD) in Ankara, one of Turkey's leading cities in terms of administrative services, is located within the borders of Çankaya explains why changes in workplace mobility trends depend on the face-covering measure (Şahin et al. 2018).

Community mobility in workplaces decreased by approximately 37% during the pre-NN era. Considering Çankaya's current position in Ankara with its employment rate, the flexibility of remote work applications may have influenced the mobility trends seen in the workplaces. As flexible and flexible working systems that are becoming widespread cause more time to be spent at home, housing preferences also differ (Henden-Şolt 2021). However, after the normalization period, the uncertainty of TRY exchange rate appeared to be strongly related to workplace mobility in Çankaya, whereas the impact of the pandemic became moderate except for the stay-at-home requirements (0.51 by DC; − 0.53 by PC).

Closures and containment policies to protect public health reduce the mobility and social interaction of individuals in local parks, national parks, public gardens, and squares in Çankaya. Park visits were largely related to weather conditions as well as pandemic-related variables according to the estimation model of the pre-normalization period. It should be noted that there is an urgent need to improve such open spaces that provide human interaction with the environment and lessen the adverse effects of pandemics on mental and physical health (Xie et al. 2020). Besides, a study conducted in the Ankara metropolitan area found that the risk level of the COVID-19 pandemic is low in areas where the population density is relatively low and the ratio of open and green spaces is relatively high (Güller et al. 2020). The preference for using public open spaces by all age and population groups for socialization during the COVID-19 pandemic deprives vulnerable members of society such as the elderly, disabled, and children to benefit from open spaces adequately. In addition to this problem, although the spatial standard for open and green spaces per person is determined as 10.00 square metres per person in the Spatial Planning and Construction Regulations of Turkey, it is 1.53 square metres per person in the study area. In the post-pandemic period, it will be beneficial to increase open and green spaces in accordance with current demand and in a way that social distancing can be maintained.

It was proved that the rise in daily mean temperature is the top variable that identifies the change in mobility in parks after the NN era. The coefficient of correlation

between mobility changes observed in parks and the temperature was found to be 0.67 by PC, whereas it was found to be 0.70 by DC, indicating a moderate relation.

There are government bodies, public organizations, embassies, educational institutions, and more than a hundred thousand workplaces in Çankaya, where the daytime population exceeds two million under normal circumstances (Şahin et al. 2014). However, community mobility in public transport stations that are used intensively during working hours decreased by approximately 37% during the pre-NN era. This change is related to travel restrictions—public transportation vehicles operating at half capacity and not accepting standing passengers—, stay-at-home requirements, school closure, workplace closure, wearing face masks, and economic responses. The study in Ankara shows that the number of monthly passengers on public transport systems, which was 1.7 million in March 2020, decreased to 1 million in September 2021 (Özcan and Hamamcıoğlu 2021). Despite the insufficient evidence for Çankaya, the new transportation preferences and travel behaviours may also have produced a drop in mobility patterns for public transit centres. A study conducted in Istanbul at the beginning of the pandemic found that people travelling less than 10 km adopted alternative modes of transport such as walking, renting an e-scooter or using a taxi, whereas those who need to travel more than 10 km tended to take personal precautions of carpooling or corporate bus services (Erbaş 2020).

The weather conditions and economic climate better explain the mobility trend of transit stations in the NN era. The depreciation of TRY, the increase in food and import prices, and the increase in transportation costs have weakened the demand for many service activities including transport, along with the COVID-19 pandemic (Central Bank of the Republic of Turkey 2021).

The shift to remote teaching led to a significant change in the mobility trends for retail and transit station locations in the pre-NN era, and that has made the retail sector more fragile. It may be essential to extend the economic support decision in case of the current mobility trends are preserved. Considering that there are 103 elementary schools, 46 secondary schools, and 13 higher education institutions in Çankaya, the dynamic student population has been unable to visit places such as shopping malls, cafés, and film theatres, which negatively affected retail expenditures. On the other hand, shopping centres, restaurants, and cafés were allowed to offer limited services under certain conditions. The fact that mobility trends in the retail sector are closely related to both the economic support index and COVID-19-induced restrictions shows that the sustainability of local enterprises depends on financial incentives. On the other hand, distance learning can increase social class inequalities as it increases dependency on digital tools (Goudeau et al. 2021).

The ability to exist economic enterprises to continue their activities in this uncertainty hinges upon adapting to the new realities of the market such as electronic commerce (e-commerce), which is also known for reducing spatial consumption inequality (Fan et al. 2018). The monthly online purchasing volumes of customers in Ankara between March 2020 and December 2021, collected by an online payment service provider in Turkey, illustrate the potential for e-commerce consumption and the growth in online retailing (Fig. 3). It can be argued that the growing trend towards the digitalization of enterprises and consumers in Turkey is related to the behavioural change caused by COVID-19 restrictions (Demirdöğmez et al. 2020). To accommodate

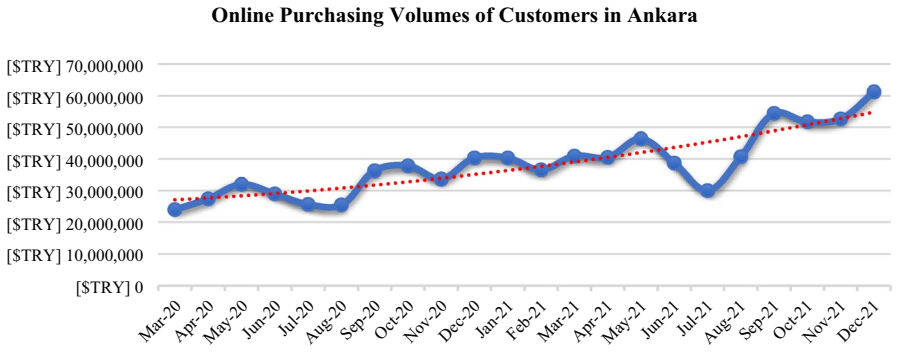


Fig. 3 The monthly online purchasing volumes of customers in Ankara (Confidential data source)

this rapid increase, logistics land uses in Ankara may need to be developed. On the other hand, it would be beneficial to explore the role of the physical retail sector in spatial planning by determining whether this growth lowers physical store sales in Çankaya. It is worth mentioning, however, that e-commerce expenditures by Ankara customers in July 2021 were on the decline. The fact that Çankaya inhabitants began to spend more time outside when restrictions were relaxed may have lowered their preference for e-commerce.

5 Conclusion

Moving around the city for access to services, work, entertainment, and socialization makes the mobility phenomenon an important sub-component of the complex urban system. Within this dynamic environment, restricting access to spaces where individuals contact each other means adding COVID-19-related indicators into the urban mobility equation. Managing the effects of the pandemic requires an understanding of human behaviour and its socio-economic context; thus, this study evaluates the factors that contribute to changes in community mobility for different urban functions during the COVID-19 pandemic. While doing this, before and after the period when the restrictions were relaxed for Turkey were discussed separately.

The aim of this paper was to identify the factors that influence changes in intracity mobility during the COVID-19 pandemic for various urban functions. In the case study conducted in Çankaya, twelve ANN models were developed to estimate changes in mobility trends for different location categories during the pre-and post-NN era. The prediction models were interpreted using distance correlation and stepwise sensitivity analysis. According to the results, it was observed that during the first sixteen months of the pandemic, the strictness of the restrictive measures in the region was at the forefront in explaining the mobility changes, while economic and weather-wise factors became more decisive in the following nine months. According to the results of the sensitivity analysis, different patterns emerged both for each urban function and for the two periods called

pre-NN and post-NN. Our first hypothesis was that the government measures were not determinative of mobility changes in every urban function. Mobility in all urban functions responded to at least one variable in the pre-NN era, which included government measures related to the pandemic. However, in the post-NN period, government measures seem to gradually lose their effect, which confirms our initial hypothesis. The other hypotheses were that the influence of the pandemic on mobility change remained in the background after the post-NN era, and that economic factors and weather conditions had an impact on urban mobility trends. Nevertheless, the daily temperature variation and the TRY exchange rate were found to be more decisive in mobility patterns in the post-NN period when looking at their relative importance and the strength of the relationship with the response variable, which confirms the other two hypotheses.

The community mobility data collected by Google are derived from possibly younger and economically advantaged mobile phone holders (Slater et al. 2021), which generates one of the limitations of the study. The fact that the study was conducted only in Çankaya caused limited implications about the widespread effect. Another limitation is that data on daily COVID-19 deceased are only available for Turkey. Lastly, the black box logic of ANN complicates establishing a cause-effect relationship between independent and response variables. To overcome this limitation, we used stepwise sensitivity analysis and ranked the importance of input variables. However, we were able to discuss only the relative importance and couldn't interpret the relationship between independent variables and the response variable comprehensively.

Making use of community mobility data to understand the spatial effects of the measures taken during the COVID-19 pandemic helps to make inferences about how the dynamism in the city can affect spatial uses. Analysing how the urban system has changed in relation to community behaviour may provide the opportunity to reveal the conditions that can accelerate social and economic recovery. It may also be a basis for managing change and developing new urban mechanisms to cope with uncertainty in the short and long term. These non-linear models, in which the complex pattern is learned, guide public policies and urban plans to develop adaptation to changing conditions by self-organization. Therefore, the results have critical implications for making sense of the complexity in the urban area, on the one hand, and adapting the space to changing daily circumstances, on the other. Contributing to the objectification of the urban features' complexity and interconnectedness is expected to result in resilient urban communities. Our effort on creating a framework to examine changes in spatial usage during the pandemic period has the potential for authorities to guide public policies on future recommendations.

Appendix

See Figs. 4 and 5 for the scatter plots of independent and response variables in the pre-and post-NN eras.

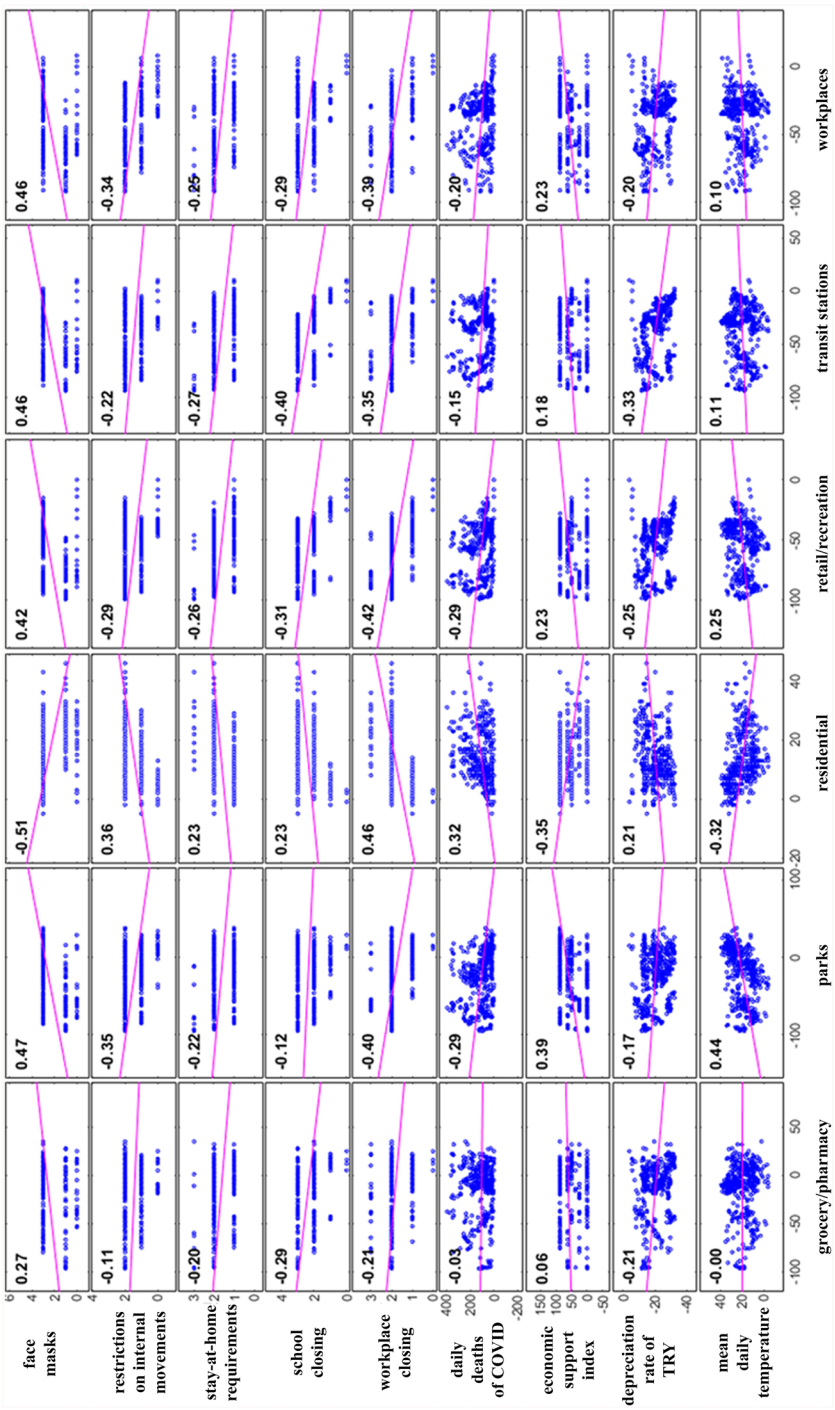


Fig. 4 Scatter plot diagrams of independent and response variables in the pre-NN era

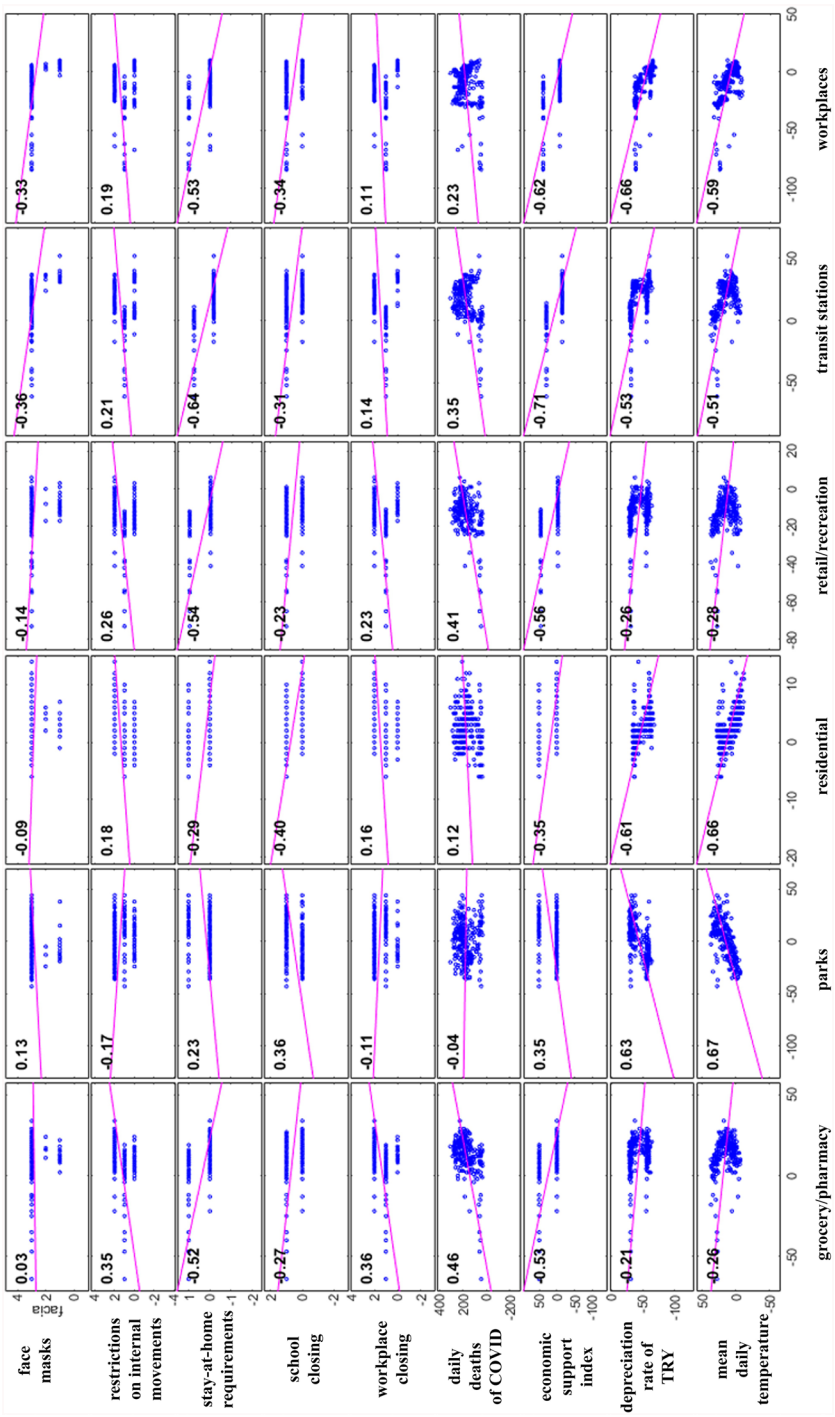


Fig. 5 Scatter plot diagrams of independent and response variables in the post-NN era

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Declarations

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this research.

Ethical approval The analysis in this research did not involve human participants or animals.

Informed consent The analysis in this research did not require informed consent from any participants.

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