Global J. Environ. Sci. Manage. 7(2): 155-170, Spring 2021

Global Journal of Environmental Science and Management
(GJESM)

Homepage: https://www.gjesm.net/

ORIGINAL RESEARCH PAPER

Using a sharing-platform to prevent a new outbreak of COVID-19 pandemic in rural areas

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ARTICLE INFO

Article History:
Received 11 August 2020
Reviewed 02 September 2020
Revised 19 September 2020
Accepted 2 October 2020

Keywords:
Coronavirus (COVID-19)
Digital contact tracing technologies (DCTT model)
Indicators
Monitoring
Rural areas
United territorial communities (UTC)

ABSTRACT

BACKGROUND AND OBJECTIVES: A new wave of Covid-19 pandemic has worsened the epidemiological situation in Ukraine. This caused the need to tighten quarantine measures that have been introduced since 31.08.2020. The conducted analysis showed that there are 3 groups of technologies for digital contact tracing: from maximum (25%) to minimum (20%). Objective of the study is to develop an exchange platform to track the spread of COVID-19 in rural areas.

METHODS: Factor analysis identified key factors of COVID-19 virus spread. Cluster analysis identified clusters of COVID-19 spread. Taxonomy method established the limits of using contact tracing methods. Discriminatory method makes it possible to change the applied contact tracing method.

FINDINGS: The results showed that the identified factors (medico-demographic special features of Covid-19 virus spread; rural infrastructure to counteract the infection) describe in total 83.24% of the data processed. Specified 4 clusters differ in the level of susceptibility of the population to COVID-19 and infrastructure development: from minimum (33% of the united territorial communities) to maximum- 13% of the united territorial communities. The value of the integral indicator calculated provides means for establishing the maximum (8.5) and the minimum (2) limit of changes in the method of digital contact tracing.

CONCLUSION: The developed methodology was implemented on the basis of the united territorial communities of Sumy region. Monitoring of changes in the epidemiological situation made it possible to justify the need to change the contact tracing model, which will reduce the epidemiological level in the region as a whole by 30%.

DOI: 10.22034/gjesm.2021.02.01

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
38	4	5

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Note: Discussion period for this manuscript open until July 1, 2021 on GJESM website at the “Show Article.

INTRODUCTION

The latest coronavirus outbreak (Lina *et al.,* 2020) is a global problem and a serious risk for the entire world population (Alanezi *et al.,* 2020; Isaifan, 2020). In view of the unusual rate of disease spread the World Health Organization (WHO) announced the beginning of the COVID-19 pandemic on 11.03.2020 (Barbosa *et al.,* 2020). The coronavirus disease in Ukraine was recorded on March 3, 2020, when the first case in Chernovtsy region was confirmed (Sitnicki *et al.,* 2020). According to Johns Hopkins University Coronavirus Resource Center, it was confirmed that as of 02.09.2020, 25.8 million people in 188 countries were infected, 857 thousand died and 13 million recovered. (CDCP, 2020). Ukraine takes 25th place (CDCP, 2020) on the global map "COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU)" by the number of registered cases of infection with COVID-19 (129 thousand cases). The tendency of prevalence rates in Ukraine is the same as in the world: 75 thousand people recovered and 2.7 thousand died during this period, 14 thousand people have mild cases (98%), 304 (2%) are in a critical condition (CDCP, 2020). As shown in the abovementioned data the global risk of death (CFR) makes 5.71% and the recovery rate is 50% (CDCP, 2020; da Rocha *et al.,* 2020). Fear of the pandemic has led to a global panic, as a result of which all countries of the world got in an emergency situation (Teslya *et al.,* 2020). As noted by the world's leading scientists (Prem *et al.,* 2020), an irrational response to the virus has had a significant negative impact on people's lives (Dimaschko, 2020) and economy of the countries. Fortunately, all the measures that were taken at the same time around the world resulted in a positive effect (Wang *et al.,* 2020. However, there is a very high risk of a second wave of pandemic (Harko *et al.,* 2014). This is related to the fact that there is SARS-CoV-2 (Coronavirus 2 with severe acute respiratory syndrome) in some countries in the red zone of disease spread; certain restrictions on preventing the risk of infection have been prematurely cancelled; there is still no medicine or effective vaccines against the COVID-19 virus (Lee *et al.,* 2020); subsequent mutation of the virus is possible. These circumstances bring much pressure to bear upon on public health system, and there is an increasing demand for different resources; technical (Fang *et al.,* 2020) and information tools to prevent the spread of the disease (Fang *et al.,* 2020), medical personnel (Dimaschko, 2020), medication and medical facilities (Ding *et al.,* 2020), means of care for seriously ill people (Chire, 2020), etc. In order to protect the society from the virus, it is necessary to take measures related not only to physical distance (Chire, 2020, but also to use information technology to break the transmission chains and to reduce the spread of SARS-CoV-2 (Darwish *et al.,* 2020). Scientists began to develop digital tools to improve control of infectious diseases and epidemics with severe consequences even before the COVID-19 pandemic (Danquah *et al.,* 2019). However, they were mainly used to facilitate records management. The pace and scale of the COVID-19 pandemic (Davis *et al.,* 2020) required the development of fundamentally new information technologies (Reyes *et al.,* 2020) with full digitization (Teslya *et al.,* 2020) or computer-aided contact tracing. At present there are three radically different technologies and digital contact tracing platforms (Table 1). The CDCP (Center for Disease Control and Prevention) has published preliminary evaluation criteria and results of the use of contact tracing tools for active surveillance over the spread of COVID-19 (CDCP, 2020).

In general, all the technologies and platforms currently used for DCTT for active surveillance over the spread of COVID-19 can be combined into three: the first - the maximum centralized approach (example: data collection by the governments of China, South Korea (Kraemer *et al.,* 2020; Lina *et al.,* 2020; Prem *et al.,* 2020; Lee *et al.,* 2020); the second - a minimum decentralized approach (proximity tracking for privacy protection in Germany, Austria, some states of America (Teslya *et al.,* 2020; Martin *et al.,* 2020; Ding *et al.,* 2020; Means *et al.,* 2020); the third - an intermediate approach. When using the third intermediate approach, manual contact tracing is supplemented by digital data collection. There are two options for using this approach: voluntary transmission of proximity data: Denmark (Schmidt-Kraepelin *et al.,* 2020), and GPS location data to public health authorities: Singapore, Taiwan (Wang *et al.,* 2020); integration of scanned QR codes from the cell phones: Australia (Ferretti *et al.,* 2020), New Zealand (Baker *et al.,* 2020), Brazil public transport (De Biazi, 2020), face recognition cameras, credit card transactions, social networks: India (Pal *et al.,* 2020). The second option is Privacy Proximity Tracking (PPT) using Bluetooth Low Energy (BLE) handshakes, saving information in phones as anonymous "beacons" without re-identifying users, and notifying potentially infected users of contact (Davis *et al.,* 2020). All the variety of approaches used aims to achieve a balance between technological feasibility, public health benefits, and user privacy protection. Data storage in the approaches used is possible in two

Table 1: The most common digital technologies and platforms tracking contacts for active surveillance over the spread of COVID-19

Intervention type	App name	Developer or country	Purpose, technologies used	Data storage	Participation	Government access	References
Max	WeChat / Alipay	China	Proximity - based exposure notification Bluetooth LE, GPS	Centralized	Mandatory (actually or functionally)	Data comes from government sources, location data sent to police	Kraemer *et al.,* 2020
Max	Safe Korea	Korea	Proximity - based exposure notification Bluetooth LE, GPS	Centralized	Mandatory (actually or functionally)	Data collection in the centralized database by the Ministry of Internal Affairs and Security to ensure compliance with quarantine orders and trace possible contacts	Lee *et al.,* 2020
Max	Shin Bet	Israel	Collecting metadata about contacts Sending text messages to identified individuals about the need for quarantine GPS based	Centralized	Central mandatory mass surveillance	Centralized system of forced data collection for tracking COVID-19 cases	Oliver *et al.,* 2020
Max	Pokemon Go	Taiwan	By Health Authorities; Transparent GPS based	Centralized	Central mandatory mass surveillance	Centralized system of forced data collection for tracking COVID-19 cases	Wang *et al.,* 2020
Max	Stay Home Safe	Hong Kong	Quarantine enforcement	Centralized	Central mandatory mass surveillance	The Government of the Hong Kong Special Administrative Region	Mello *et al.,* 2020
Max / Middle	ProteGO Safe	Poland	Contact tracing, medical reporting, information BLE or QR Based	Centralized / Decentralized	Voluntary app: Centralized model	Ministry of Digital Affairs of Poland: Mandatory "checks" by public health authorities, fixing a waypoint using GPS, sending "selfies" photos to the controlling agency for quarantine compliance	Woldaregay *et al.,*2020
Max / Middle	StopCovid ROBERT (ROBust and privacy-presERving proximity Tracing protocol)	France	Contact tracing, BLE or QR Based	Centralized	Voluntary app: Centralized model	Government of France, French National Assembly	Bansal *et al.,* 2020
Max/ Middle	Smittestop	Denmark	Contact tracing, BLE or QR Based	Centralized / Decentralized	Voluntary app: Centralized model	Ministry of Health and the Elderly, the Danish Agency for Patient Safety, the National Board of Health, the Danish Serum Institute, the National Board of Digitization and Netcompany	Schmidt-Kraepelin *et al.,* 2020

Continued Table1: The most common digital technologies and platforms tracking contacts for active surveillance over the spread of COVID-19

Intervention type	App name	Developer or country	Purpose, technologies used	Data storage	Participation	Government access	References
Middle ground	Blue Trace	Singapore	Digital contact tracing (DCTT) Bluetooth LE	Decentralized	Voluntary / opt-in	Mandatory government access if positive	Reyes *et al.*, 2020
Middle ground	Coronavirus Australia COVIDSafe	Australia	DCTT BLE or QR based	Centralized / Decentralized	Information, isolation registration; contact tracing	Australian Department of Health	Ferretti *et al.*, 2020;
Middle ground	NZ COVID Tracer	New Zealand	Scan QR codes to track for contract tracing purposes	Centralized / Decentralized	Voluntary app: Centralized model	The Health Ministry	Baker *et al.*, 2020
Middle ground	NHSX/Oxford; COVID Symptom Study, formerly Covid Symptom Tracker; NHS COVID-19	England	DCTT Bluetooth LE; SMS	Centralized / Decentralized	Voluntary / opt-in; self-diagnostic; multipurpose	Government maintains data, but no storage	Lewnard *et al.*, 2020
Middle ground	SwissCovid	Switzerland	DCTT Bluetooth LE, GPS DP-3T protocol	Decentralized	Voluntary / opt-in	Matching of proximity encounters happens locally on individuals' devices: Decentralized Privacy-Preserving Proximity Tracing (DP-3T) protocol or the Google-Apple Exposure Notification API	Li *et al.*, 2020
Middle ground	Aarogya Setu	India	DCTT Bluetooth LE, GPS	Centralized / Decentralized	Voluntary / opt-in	Anonymized, aggregate	Pal *et al.*, 2020;
Minimal	Care19	North Dakota USA	Proximity - based exposure notification DCTT Bluetooth LE, GPS	Centralized / Decentralized	Voluntary / opt-in	In aggregate, optional if positive	Means *et al.*, 2020
Minimal	Immuni	Italy	Proximity - based exposure notification; proximity tracing and exposure notification, optional GPS location sharing DCTT Bluetooth LE	Decentralized	Voluntary / opt-in	Ministry of Health, the Ministry for Technological Innovation and Digitalization use public infrastructures located within the national borders	Teslya *et al.*, 2020
Minimal	Stopp Corona	Austria	Proximity - based exposure notification Bluetooth LE	Decentralized	Voluntary / opt-in	Federal Ministry of Health contact tracing, medical reporting	Martin *et al.*, 2020
Minimal	ito	Germany	Proximity - based exposure notification Bluetooth LE, GPS	Decentralized	Voluntary / opt-in	None, positive results to ito server	Ding *et al.*, 2020

ways: centralized storage of impersonalized data; and decentralized storage of personally identifiable data. Ukraine is included into the red zone of COVID-19 prevalence. The degree of incidence for COVID-19 is varying in the studied Sumy region (Fig. 1).

Since the level of COVID-19 infection in rural areas of the Sumy region is varying (Fig. 1), it is necessary to justify the use of a reasonable approach to DCTT for active surveillance and to stop the spread of COVID-19 for each group of rural areas. The main

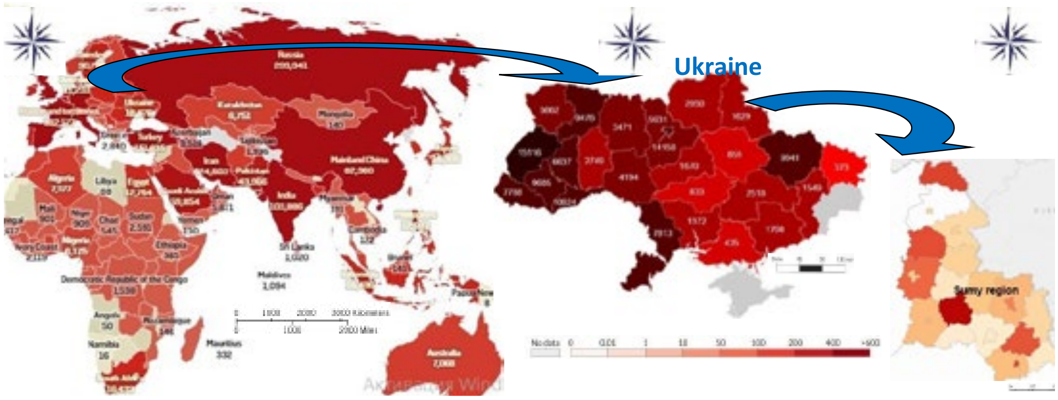


Fig. 1: COVID-19 infection level in rural areas of Sumy region, Ukraine

objective of this study is to analyze the existing DCTT methods and choose the best method to track contacts and reduce the COVID-19 infection level in rural areas of Sumy region of Ukraine. This study was conducted taking into account the data on COVID-19 infection level in 30 United Territorial Communities of rural areas of Sumy region of Ukraine for the period from April 2020 to August 2020 at runtime.

MATHERIALS AND METHODS

Materials description

The history of the epidemic started in different countries at different times. The COVID-19 spread diagram for each country with the same starting point makes it possible to compare the spread of COVID-19 in different countries (Fig. 2). The starting point for this diagram is the day when the country confirmed 100th case of infection. Trend lines represent the number of days that have passed since this event. The diagram shows the number of confirmed COVID-19 cases per 100,000 population in each country.

The first case of COVID-19 in Ukraine was registered on 03.03.2020. 198.634 total cases of COVID-19, 3.130 new cases of disease, 3.959 deaths were registered in Ukraine as of 27.09.2020. The average number of cases per 1 million population makes 4,549, the average number of deaths per 1 million population makes 91. The population of Ukraine makes 43,669,439 people. The State Commission for Technological and Environmental Safety and Emergency Situations of Ukraine decided to establish the levels of epidemic danger of COVID-19 spread by October 31, 2020. The "red" quarantine

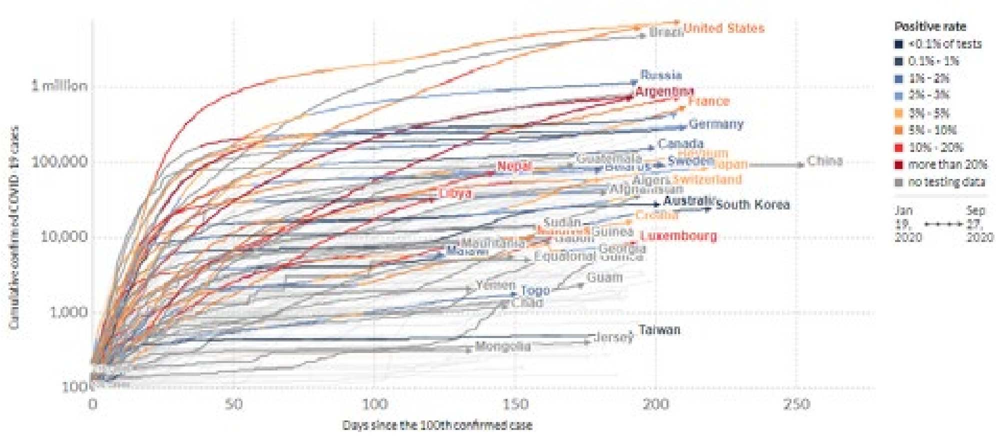


Fig. 2: Confirmed COVID-19 cases in total (CDCP, 2020)

zone included certain cities and rural areas of five Ukrainian regions: Ivano-Frankivsk, Odessa, Rivne, Ternopil and Chernivtsi. The "orange" zone included the cities of Lutsk, Uzhgorod, Lviv, Sumy, Ternopil and Kharkiv (Fig. 1). According to the data as of 28.09.20 there were only 3813 infected cases, 63 (1,7%) fatal cases, 1641 (43,0%) recovered, and 2109 (55,3%) diseased people in the studied region of Sumy. The "orange" zone of epidemic danger includes Sumy District (235 diseased, 5 deceased, 91 recovered); Konotopsky District (215 diseased, 6 deceased, 10 recovered); Bilopolsky District (117 diseased, 2 deceased, 61 recovered); Krolevetsky District (108 diseased, 2 deceased, 93 recovered). "Yellow" level was set in Shostkinsky District (106 diseased, 5 died, 55 recovered); Trostyanetsky District (90 diseased, 4 deceased, 74 recovered); Akhtyrkinsky District (98 diseased, 1 deceased, 78 recovered); Nedrigaylovsky District (80 sick, 1 died, 66 recovered); Romny District (58 diseased, 2 deceased, 33 recovered); Burynsky District (27 diseased, 2 deceased, 12 recovered); Konotopsky District (60 diseased, 3 died, 47 recovered). The rest of the districts are in the "green" zone of epidemic danger (Fig. 1). Based on the established levels of epidemic hazard of COVID-19 spread, the anti-epidemic measures on the territory of Sumy city local community were stepped up. Organizational measures were taken in Krolevetskaya, Nedrigailovskaya, Sumy and Trostyanetskaya communities to ensure that the population and business entities complied with the anti-epidemic requirements on the respective territories. The following activities are prohibited (Grossman *et al.*, 2020): activities of means of accommodation (hostels, tourist bases, etc.), except for hotels; activities of entertainment facilities, restaurants at night time; planned hospital admission; activity of gyms, fitness centers and cultural institutions; new admission to children's camps; restrictions for public events: 1 person per 20 square meters and not more than 100 people. The current epidemiological situation requires justification for differential application of DCTT models. Initial data to assess the resistance level of rural areas of Sumy region to COVID-19 are given in Table 2. The study base consisted of 13 indicators for 7 months of quarantine (March 2020 – September 2020) in Sumy region.

Initial data processing (Table 2) using the developed methodology will make it possible to make a reasonable choice of a model of COVID-19 prevalence contacts tracking for each rural area.

Methods description

Analysis of literature sources has confirmed that the use of DCTT models has proven its efficiency in preventing the spread of COVID-19. The conducted review makes it possible to assert that for rural areas with low spread of COVID-19 and mortality rates it is sufficient to use the minimum DCTT method, for areas with medium infection rate of COVID-19 - middle ground DCTT model, for areas with high infection rate of COVID-19 - maximum ground DCTT model. The first stage included the use of factor analysis. This method makes it possible to identify the most significant indicators affecting the COVID-19 infection rate and mortality in rural areas. The rows of the final table of factor analysis are equal to the number of indicators, the columns - to the number

Table 2: System of indicators affecting the resistance level of COVID-19 in rural areas of Sumy region

Indicators	Symbol
population density (number of residents per 1 sq. km)	x_1
Proportion of children under 7 years of age (% of total population)	x_2
Proportion of residents over 65 years of age (% of the total number of residents)	x_3
Proportion of youth aged 20-35 years (% of total population)	x_4
mortality rate from COVID-19 (number of deaths divided by the number of confirmed cases)	x_5
mortality per 100,000 people of local population	x_6
number of confirmed cases of COVID-19 per 100,000 of local population	x_7
number of recovered from COVID-19 per 100,000 of local population	x_8
number of educational, cultural and sports infrastructure facilities per 100,000 of local population	x_9
number of health and recreation infrastructure facilities per 100,000 people	x_{10}
proportion of enterprises operating online (% of the total number of enterprises on the territory)	x_{11}
proportion of online workers (% of the total number of local working population)	x_{12}
Number of medical personnel per 100,000 of local population	x_{13}

of factor loads of indicators. Factor loads reflect the correlation (dependence) of indicators and factors, red color shows to which factor the indicator refers, sign (+) shows direct impact, sign (-) shows negative impact. This study identified 2 factors. The first one reflects the demographic situation in the studied Sumy region, i.e. the degree of physiological susceptibility to COVID-19. The second factor reflects the infrastructural readiness of rural areas to resist infection (Lipsey *et al.,* 2000). The factor analysis was conducted by means of STATISTICA program. In general, the situation of combatting COVID-19 is described as the resistance of rural areas to the spread of COVID-19 depending on two factors: demographic situation and infrastructure development of the area using Eq. 1.

$$Cov_i = \sum_{j=1}^{N} F_j \qquad (1)$$

Where, Cov_j reflects the stability of the *i*-territory; F_j- *j*-factor (demographic / infrastructural aspect of susceptibility / resistance to COVID-19); *N* - number of factors identified. The value of each factor (susceptibility / resistance to COVID-19) is determined using Eq. 2.

$$F_j = \frac{1}{Expl.F_j} \times \sum a_{ij} \times X_{ij} \qquad (2)$$

Where, $Expl.F_j$ is the factor load *j* - the susceptibility / resistance aspect of COVID-19; a_{ij} is the value of the indicator X_{ij}; X_{ij} is the *ij* indicator.

Cluster analysis of K-average was used at the second stage to justify the division of rural areas into groups by the level of prevalence and susceptibility of population to COVID-19.

The methodology of using K-average cluster analysis is as follows:

- Prior conversion of all indicators to a dimensionless form using Eq. 3.

$$z_{ij} = \frac{x_{ij} - \overline{x}_j}{S_j} \qquad (3)$$

Where, x_{ij} is the *j*-th COVID-19 spread indicator of the *i*-th rural area; x_j is the average of this indicator for all rural areas; S_j is the standard deviation of this indicator for all rural areas.

- Minimizing the standard deviation of all indicators from the center of the identified clusters using Eq. 4 (Lipsey *et al.,* 2000).

$$min\ [\sum_{i=1}^{k} \sum x(j) \in S_i \left\| x^{(j)} - \mu \right\|^2] \qquad (4)$$

где $x^{(j)} \in R^n$; $\mu_i \in R^n$; μ_i – cluster centroid R_i.

- Determination of the R_i cluster centroid (center) by maximizing the distances between clusters and minimizing the standard deviation of indicators from the cluster centroid. Calculation of the centroid of each R_i cluster using Eq. 5.

$$\mu_i = \frac{1}{S_i} \sum_{x^{(j)} \in S_i} x^i \qquad (5)$$

- Completion of recalculation when μ_i values do not change, using Eq. 6.

$$\mu_i^{step\ t} = \mu_i^{step\ t+1} \qquad (6)$$

Where, *step t* is the previous iteration, *step t+1* is the current iteration.

The method of taxonomy was used at the third stage. This method makes it possible to determine the boundary value of COVID-19 infection level for each of the clusters as an integral indicator. The stages of taxonomy:

- Matrix formation of significant indicators identified at the first stage of factor analysis (highlighted in red in the STATISTICA listing). The initial matrix has the following form using Eq. 7.

$$X = \begin{pmatrix} x_{11} x_{12} \ldots x_{1n} \\ x_{21} x_{22} \ldots x_{2n} \\ \ldots\ldots\ldots\ldots\ldots \\ x_{m1} x_{m2} \ldots x_{mn} \end{pmatrix} \qquad (7)$$

- Matrix transformation (7) to a dimensionless standardized form and matrix standard formation, Where, 0 is the best value in columns using Eq. 8.

$$x^0 = [x_1^0, x_2^0, \ldots x_n^0] \qquad (8)$$

- Determination of the multidimensional Euclidean distance from the matrix standard using Eq. 9.

$$L_i = [\sum_{i=1}^{n} (x_i - x_i^0)^2]^{1/2} \qquad (9)$$

- Determination of the average Euclidean distance from all objects to the standard using Eq. 10.

$$\overline{L} = \frac{1}{N} \times \sum_{i=1}^{N} L_i \quad (10)$$

- Determination of the standard deviation of multidimensional distances using Eq. 11.

$$\sigma = \frac{1}{N} [\sum_{i=1}^{N} \left(L_i - \overline{L} \right)^2]^{1/2} \quad (11)$$

- Calculation of the taxonomy indicator, which characterizes the resistance level of rural area COVID-19 using Eq. 12.

$$\eta_i = 1 \quad \frac{L_i}{\overline{L} + 2\sigma} \quad (12)$$

The obtained value of taxonomy indicator is interpreted as follows: the stronger is the resistance level of rural area to COVID-19, the closer is its value to 10.

The resistance level of rural area to COVID-19 was presented in the form of dendogram (modification of cluster analysis) by means of STATISTICA program. The fourth stage provided the use of discriminant analysis, which makes it possible to recognize objects to decide which indicators divide (i.e. “discriminate”) data sets (so-called “groups”). The discriminant analysis is based on the assumption that the descriptions of objects (rural areas) of each R_i cluster represent the implementation of a multidimensional random value distributed according to the normal law *Nm(μk;Σk)* with average μk and covariance matrix using Eq. 13.

$$C_k=1/(n_k-1) \sum(x_{ik}-\mu_k)^T(x_{ik}-\mu_k) \quad (13)$$

Where, the index m indicates the dimension of the feature space.

Discriminatory analysis is used in this case to monitor the need to correct the applied DCTT model. That is, whether the studied rural area remained in the same cluster or whether the data on COVID-19 resistance have changed. For this purpose, linear functions to identify to which cluster the rural area is referred are established based on the following indicators: confusion matrix in the training sample and in the cross-check, identification errors and mean square distance between the centroids of two clusters. The calculated maximum value of one of two identification functions indicates that the rural area under study is included to one of the clusters and if necessary is subject to correction used by the DCTT model.

RESULTS AND DISCUSSION

The first stage included factor analysis which was conducted to identify indicators that have an impact on the rate of COVID-19 spread and the possibility of limiting the spread of COVID-19 virus (Table 3).

Table 3: Results of factor analysis. Identification of COVID-19 virus restriction indicators (STATISTICA 10 listing)

Variable	Factor Loadings (Unrotated) (data) Extraction: Principal components (Marked loadings are > 0.700000)	
	Factor 1	Factor 2
x_1	-0.790815	-0.495010
x_2	0.745745	-0.272548
x_3	-0.753503	-0.338784
x_4	0.986729	-0.368339
x_5	-0.275268	-0.028653
x_6	-0.518377	0.016648
x_7	-0.201241	0.013647
x_8	-0.072538	0.609842
x_9	-0.272548	-0.863570
x_{10}	-0.230653	0.758107
x_{11}	-0.028653	0.863570
x_{12}	0.016648	0.916809
x_{13}	-0.595590	0.753435
Expl.Var	4.062440	2.858818
Prp.Totl	0.512495	0.319909

The first factor included 8 indicators (Table 3): population density (number of residents per 1 sq. m.). km); the proportion of children under 7 years of age (% of total population); the proportion of residents over 65 years of age (% of total population); the proportion of youth aged 20-35 years of age (% of total population); COVID-19 mortality rate (number of deaths divided by number of confirmed cases); mortality rate per 100,000 people of local population; the number of confirmed COVID-19 cases per 100,000 people of local population; and the number of recovering COVID-19 cases per 100,000 people. The second factor included the rest 5 indicators: the number of educational, cultural, and sports infrastructure facilities per 100,000 people of local population; the number of health and recreation facilities per 100,000 people of local population; the proportion of enterprises working online (% of the total number of enterprises on the territory); the proportion of population working online (% of the total number of population working online); the number of medical personnel per 100,000 people on the territory. The results of the conducted factor analysis showed that the specific features of spread and limitation of COVID-19 epidemic in rural areas of Sumy region are fully characterized by two factors obtained. This is quite enough to justify the choice of DCTT model for each rural area. The first factor can be characterized as medical-demographic features of COVID-19 virus spread. It describes 51.25% of the dispersion and has the greatest impact on the epidemiological situation in rural areas. The second factor describes 31.99% of the dispersion. It characterizes the infrastructural condition of rural areas of the given territory, and socio-cultural diversification of the territory has a negative impact on limiting the spread of COVID-19 (because of the concentration of people at a single location). Other indicators of the second factor have a positive impact on limiting the spread of COVID-19 (due to the possibility of organizing social distance or providing medical care). According to Table 3, the first factor's impact on limiting COVID-19 spread is described in Eq. 14.

$$F_1=1/4.062440 \cdot (-0.790815\, x_1 + 0.745745\, x_2 -0.753503\, x_3 +0.986729\, x_4 -0.275268\, x_5 -0.518377\, x_6 -0.201241\, x_7 -0.072538\, x_8) \quad (14)$$

The value of the impact of the second factor on the possibility of limiting the spread of COVID-19 is determined by Eq. 15.

$$F_2=1/2.858818 \cdot (-0.863570\, x_9 + 0.758107\, x_{10} + 0.863570\, x_{11} + 0.916809\, x_{12} + 0.753435\, x_{13}) \quad (15)$$

Thus, the obtained model reflects completely the level of population's susceptibility to COVID -19 in the studied region according to two factors, the first one reflects medical-demographic peculiarities of COVID -19 virus spread in the given area, the second one represents infrastructural limitations of COVID -19 spread K-average cluster analysis was used at the second stage to justify the division of rural areas into groups according to the level of prevalence and susceptibility of population to COVID-19. The diagram of K-average is shown in Fig. 3.

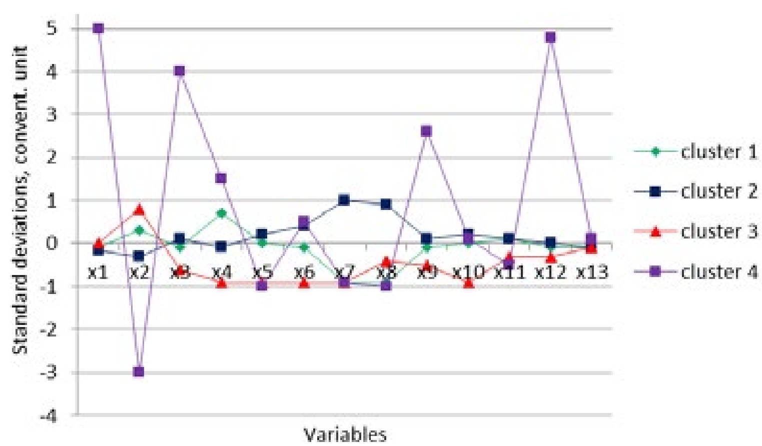


Fig. 3: Diagram of average values of indicators for the prevalence rates and susceptibility level of population to COVID-19 in rural areas of Sumy region

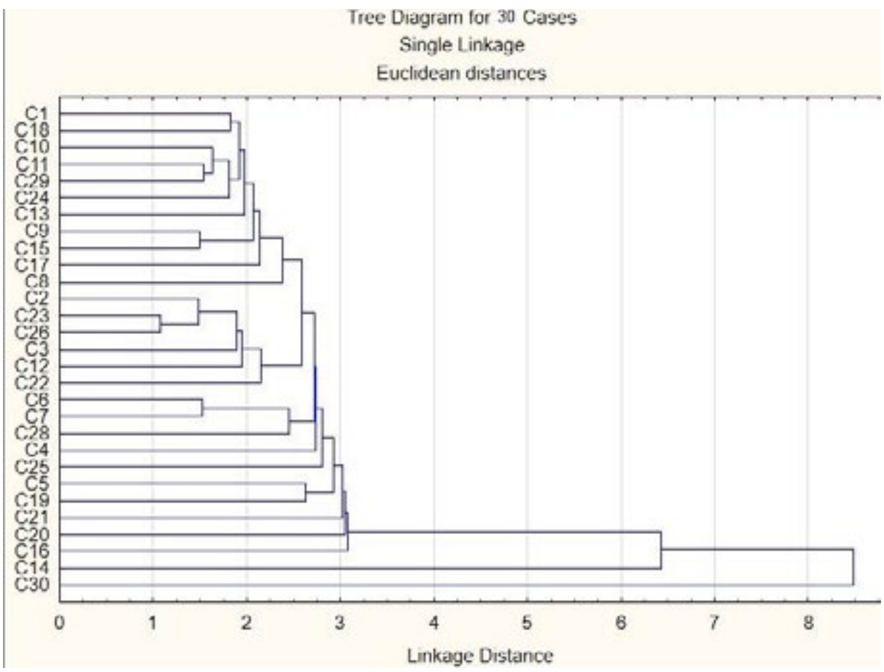
Fig. 3 shows that in accordance with the prevalence rates and susceptibility level of population to COVID-19 all the rural areas of Sumy region are divided into four clusters. The number and composition of united territorial communities (UTC), which are part of the obtained clusters, is presented in Table 4.

As the data in Table 4 show according to the identification feature: "UTC resistance level / susceptibility of population to COVID-19": cluster 1 includes UTC, where there is a low level of susceptibility of population to COVID-19 due to the small number of categories with the increased risk of infection (elderly people, children, chronic patients with compromised immune system), middle adulthood and young population prevail. Besides, there is a low level of infrastructure development, i.e., few enterprises providing services to the population (cafes, restaurants, entertainment facilities). Comparison of the first cluster identified by the model used in this study in real time mode confirms the fact that on the territory of UTC of the first cluster (Andriyashivska UTC, Bochechkivska UTC, Vilshanska UTC, Druzhbivska UTC, Dubovyazivska UTC, Kyrykivska UTC, Krasnopilska UTC, Mykolayivska (Bilopil district) UTC, Stepanovskaya UTC, Shalyhynska UTC) from the total population in Andriyashivska UTC (4,000 people - minimum) to 7.3 thousand people in Stepanovskaya UTC (maximum) - the proportion of the population aged 25 to 45 years makes 52%. Furthermore, the number of infrastructure entertainment facilities ranges from 5 facilities in Andriyashivska UTC (1.25 facilities per 1 thousand population) to 9 facilities in Stepanovskaya UTC (1.23 facilities per 1 thousand population). UTC, which were included in cluster 2, also have poorly developed infrastructure, but they

Table 4: Cluster analysis results. Determination of UTC cluster composition in Sumy region of COVID-19 virus spread (STATISTICA 10 listing)

United territorial communities (UTC) of Sumy Region	Cluster/ quantity UTC	Identification of susceptibility and resistance level of local population to COVID-19
Andriyashivska UTC Bochechkivska UTC Vilshanska UTC Druzhbivska UTC Dubovyazivska UTC Kyrykivska UTC Krasnopilska UTC Mykolayivska (Bilopil district) UTC Stepanovskaya UTC Shalyhynska UTC	1 /10	Low susceptibility of population to COVID-19 Low level of infrastructure development
Bilopilska UTC Berezivska UTC Boromlyanska UTC Znob-Novgorod UTC Mykolayivska UTC Myropilska UTC Nyzhnosyrovatska UTC Novoslobodskaya UTC Khotyn UTC	2 /9	Average susceptibility of population to COVID-19 Low level of infrastructure development
Burynska UTC Verkhnosyrovatska UTC Grunska UTC Korovynska UTC Chupakhivska UTC Shostkinskaya UTC Chernechchynska UTC	3/7	Average susceptibility of population to COVID-19 Average level of infrastructure development
Krolevets UTC Nedrigailivska UTC Trostyanetska UTC Sumy UTC	4/4	High level of susceptibility of population to COVID-19 High level of infrastructure development

have a higher level of perception of COVID-19, as the number of elderly people is higher in this area. Besides, the actual data collected from the place of research practice confirms the fact that on the territory of UTC of the second cluster (Bilopilska UTC, Berezivska UTC, Boromlyanska UTC, Znob-Novgorod UTC, Mykolayivska UTC, Myropilska UTC, Nyzhnosyrovatska UTC, Novoslobodskaya UTC, Khotyn UTC) from the total population (from 3 to 3). 6 thousand people in Bilopilska UTC (minimum) to 5.5 thousand people in Khotyn UTC (maximum) - the proportion of the population over 60 years is on average 58%. At the same time, there are also few infrastructure facilities of entertainment nature: from 3 facilities in Bilopilska UTC (0.83 objects per 1 thousand population) to 4 facilities in Khotyn UTC (0.72 objects per 1 thousand population). Cluster 3 is characterized by an average level of susceptibility of the population to COVID-19 (middle age population prevails), an average level of infrastructure development (more enterprises and residents working online in comparison with the first and second clusters). The actual data collected from the place of research practice confirms as well the fact that on the territory of UTC of the third cluster (Burynska UTC, Verkhnosyrovatska UTC, Grunska UTC, Korovynska UTC, Chupakhivska UTC, Shostkinskaya UTC, Chernechchynska UTC) the population aged 45-60 years (from 10 years) prevails. 2 thousand people in Chernechchynska UTC (minimum) to 14 thousand people in Burynska UTC (maximum) - the proportion of the population aged 45-60 years makes 47%. At the same time, the number of infrastructure entertainment facilities is as follows: 12 facilities in Burynska UTC (0.86 objects per 1 thousand population) to 14 facilities in Burynska UTC (1 object per 1 thousand population), the proportion of population working online is on average 33%. Cluster 4 is characterized by a high level of susceptibility of population to COVID-19 and a high level of infrastructure development. The actual



Symbols of united territorial communities: Krolevets: Andriyashivska UTC C_1; Bilopilska UTC C_2; Berezivska UTC C_3; Boromlyanska UTC C_4; Bochechkivska UTC C_5; Burynska UTC C_6; Verkhnosyrovatska UTC C_7; Vilshanska UTC C_8; Grunska UTC C_9; Druzhbivska UTC C_10; Dubovyazivska UTC C_11; Kyrykivska UTC C_12; Korovynska UTC C_13; Trostyanetska UTC C_14; Mykolayivska (Bilopil district) UTC C_15; Krolevets UTC C_16; Mykolayivska C_17; Myropilska UTC C_18; Nyzhnosyrovatska UTC C_19; Nedrigailivska UTC C_20; Novoslobodskaya UTC C_21; Stepanovskaya UTC C_22; Krasnopilska UTC C_23; Khotyn UTC C_24; Chupakhivska UTC C25; Shalyhynska UTC C_26; Shostkinskaya UTC C_27; Znob-Novgorod UTC C_28; Chernechchynska UTC C_29; Sumy UTC C_30.
9.

Fig. 4: Integral indicator of resistance and prevalence rates of COVID-19 of the united territorial communities of Sumy region

Table 5: Results of discriminant analysis. Monitoring of changes in the epidemiological situation COVID-19 in rural areas of Sumy region (STATISTICA 10 listing)

Discriminatory function of changing the epidemiological situation of COVID-19 of the *i*-th cluster	DCTT model usage condition for UTC *i*-th cluster residents	Suggested DCTT methods of COVID-19 new pandemic outbreak prevention platform
$Int_1 = 0.262 - 0.81x_1 + 0.74x_2 - 0.75x_3 + 0.98x_4 - 0.27x_5 - 0.51x_6 - 0.21x_7 - 0.07x_8 - 0.86x_9 + 0.75x_{10} + 0.86x_{11} + 0.91x_{12} + 0.75x_{13}$	$Int_1 = max$	For the residents of UTC *i*-th cluster it is suggested using the minimum methods of contact tracing: manual notification of the case of COVID-19 by phone, sms-notifications.
$Int_2 = 0.321 - 0.73x_1 + 0.83x_2 - 0.62x_3 + 0.99x_4 - 0.19x_5 - 0.42x_6 - 0.19x_7 - 0.06x_8 - 0.77x_9 + 0.82x_{10} + 0.83x_{11} + 0.92x_{12} + 0.79x_{13}$	$Int_2 = max$	For the *i*-th cluster it is suggested using medium-minimal methods of tracking contacts: manual notification of COVID-19 cases by phone, sms-notifications; voluntary service of people who had contact with the carrier COVID-19.
$Int_3 = 0.428 - 0.69x_1 + 0.86x_2 - 0.59x_3 + 1.02x_4 - 0.17x_5 - 0.40x_6 - 0.17x_7 - 0.05x_8 - 0.75x_9 + 0.88x_{10} + 0.88x_{11} + 0.93x_{12} + 0.81x_{13}$	$Int_3 = max$	For the *i*-th cluster it is suggested using the average methods of tracking contacts: automatic notification of COVID-19 cases, verification of quarantine conditions by public health authorities, fixing the waypoint using GPS, sending "selfies" photos to the controlling agency for quarantine compliance.
$Int_4 = 0.555 - 0.59x_1 + 0.88x_2 - 0.49x_3 + 1.03x_4 - 0.13x_5 - 0.37x_6 - 0.13x_7 - 0.03x_8 - 0.66x_9 + 0.98x_{10} + 0.98x_{11} + 0.99x_{12} + 0.88x_{13}$	$Int_4 = max$	For the residents of UTC *i*-th cluster it is suggested using the most stringent methods of tracking contacts: automatic notification of COVID-19 cases, centralization of information in the UTC administration, public health authorities, forced examination of people who had contact with the carrier COVID-19.

data collected from the place of research practice confirms as well the fact that on the territory of UTC of the fourth cluster (Krolevets UTC, Nedrigailivska UTC, Trostyanetska UTC, Sumy UTC) the population aged 45-60 years prevails (from 8.5 thousand people in Nedrigailivska UTC (minimum) to 78.8 thousand people in Sumy UTC (maximum) - the proportion of population aged 45-60 years makes 44%. At the same time, the number of infrastructure entertainment facilities is as follows: 12 facilities in Nedrigailivska UTC (0.86 facilities per 1 thousand population) up to 54 facilities in Sumy UTC (0.7 facilities per 1 thousand population), the proportion of population working in the remote mode is on average 13%. This situation is explained by the fact that the fourth cluster includes UTC, located near large cities, transport highways, highly developed infrastructure, a large number of critical population groups (Kolodiziev *et al*., 2018). Previous studies have shown that refugees living in rural areas near large cities have an additional social burden (Shcherbak *et al*., 2020). All these factors certify that these four clusters require applying different models of tracking contacts with COVID-19 patients. In other words, it is necessary to offer a comprehensive platform to prevent a new outbreak of COVID-19 pandemic with differentiation of COVID-19 contact tracing models by different UTC clusters. Integral COVID-19 prevalence rate indicators for each of the clusters were calculated at the third stage by means of taxonomy using equations 7 - 12. The value of the integral COVID-19 prevalence rate indicator shows the boundary where one contact tracing model is transformed into another model. COVID prevalence rate indicator of different UTCs was presented in the form of a dendogram (Fig. 4) by means of STATISTICA software.

Fig. 4 show that the closer the COVID-19 integral value is to 10, the more stringent measures to track contacts with COVID-19 carriers are required. The last stage included the use of discriminant analysis. It was used to monitor the dynamics of the epidemiological situation in the identified clusters. If the situation worsens or improves, it is necessary to change the means of tracking contacts with COVID-19 carriers used. The result of the conducted discriminant analysis is given in Table 5.

The use of the suggested discrete method to monitor the situation of spread of COVID-19 makes it possible to: identify possible deterioration (improvement) of the situation, quickly and efficiently propose changes in the methods of tracking contacts COVID-19 and appropriate quarantine measures.

It is suggested to use discriminant analysis in case of need to choose and modify the contact tracing model. It is suggested to monitor the status COVID-19 spread on a weekly basis using the indicators of the developed model. New actual data are substituted in 4 discriminant equations. Each equation corresponds to one of the four contact tracing methods. Maximum value of the integral indicator of the discriminant equation shows the need for an appropriate contact tracing method. Testing of the suggested model has proved that timely change of the used COVID-19 contact tracing method will reduce the epidemiological level by 30% as a whole.

CONCLUSION

The conducted analysis of existing methods of response to COVID-19 pandemic has shown that traditional methods need to be complemented by digital technologies that facilitate epidemiological surveillance of public health and tracking of contacts. Technologies and platforms for digital contact tracing can be roughly categorized into three groups: the maximum approach (central government data collection), applied in 25% of countries; the minimum approach (decentralized confidentiality and contact notification), applied in 20% of countries; various options for the intermediate approach (supplementing manual contact tracing with digital data collection that can be transferred to public health authorities), applied in most countries that is 65%. The analysis confirms that there is no one-size-fits-all approach to DCTT. Technology design should not be static, but it should be able to develop depending on local conditions, new data and changing preferences and priorities. This prerequisite was the basis for the sharing-platform developed to track over the spread and resistance of COVID-19 in rural areas. The proposed methodology was tested in rural areas of Sumy region. The use of the suggested platform is based on the methodology consisting of four stages. The first stage provides identification of the most significant indicators affecting the epidemiological situation by means of factor analysis. These indicators are grouped into 2 factors. The first factor reflects the medical-demographic features of the COVID-19 virus spread, and reasons 51.25% of the dispersion. The second factor reflects the infrastructural readiness of rural areas to resist the infection, reasons 31.99% of the dispersion. At the second stage, 4 clusters were identified by the level of susceptibility of the population and the level of resistance of UTC to COVID-19 by means of K-average cluster analysis. The identified clusters reflect the current epidemiological situation in rural areas of Sumy region. In 33% of UTC of the first cluster there is a low level of susceptibility of population to COVID-19 and low level of infrastructure development. In 30% of UTC of the second cluster there is an average level of susceptibility of population to COVID-19 and low level of infrastructure development. In 24% of UTC of the third cluster there is an average level of susceptibility of population to COVID-19 and a low level of infrastructure development. In 13% of UTC of the first cluster there is a high level of susceptibility of population to COVID-19 and a high level of infrastructure development. In the third stage, the boundary value of COVID-19 prevalence rates for each cluster was determined by the taxonomy method as an integral indicator. The calculations showed that the maximum value of the integral indicator is observed in Sumy UTC (8.5), the minimum is found in Andriyashivska UTC (2). The fourth stage provides using discriminant analysis, by means of which we monitor changes in the epidemiological situation of COVID-19 in rural areas of Sumy region and, if necessary, correct the applied DCTT model. The maximum value of discriminant function shows to which cluster UTC is referred and which tracking system of contacts and quarantine measures should be applied/changed. Interactive use of the sharing platform makes it possible to improve the system of tracking the spread and resistance of COVID-19 in rural areas of Sumy region by 30%, which improves the epidemiological situation in the region as a whole.

AUTHOR CONTRIBUTIONS

V. Shcherbak substantiated the study methodology, validation, conceptualization, I. Gryshchenko supervised the interaction with the administration of rural areas of Sumy region, L. Ganushchak-Yefimenko collected and analyzed literature, O. Nifatova collected data on epidemiological situation in Sumy region, state of infrastructure on the territory of the united territorial communities, V. Tkachuk wrote the initial project plan, T. Kostiuk provided software for information processing, V. Hotra calculated models and presented a graphical presentation of the material.

ACKNOWLEDGEMENT

The authors express their gratitude to the heads and residents of the united territorial communities of

Sumy region, Sumy regional administration for their assistance in organizing and conducting the fieldwork.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

ABBREVIATIONS

%	Percentage
Aarogya Setu	Special electronic contact tracking application in India
AIDS	Acquired immune deficiency syndrome
BLE	Bluetooth (wireless data transfer protocol) with low power consumption
Bluetooth LE	Low power wireless data transfer protocol
BlueTrace	Special electronic contact tracking application in Singapore
Care19	Special electronic contact tracking application in New Dakota USA
CDCP	Center for Disease Control and Prevention
CFR	Global risk of death
Coronavirus_ Australia *COVIDSafe*	Dedicated electronic contact tracking application in Australia
COVID-19	COronaVIrus Disease 2019, coronavirus infection 2019-nCoV
CSSE	Center for Systems Science and Engineering
DCTT	Digital contact tracing technologies
DP-3T protocol	Bluetooth contact chain tracking protocol to prevent coronavirus proliferation SARS-CoV-2
Eq.	Formula of calculation
Expl.Var	Explanatory Variable
Fig.	Figures
GPS	System of global positioning
JHU	Johns Hopkins University
Immuni	Special electronic contact tracking application in Italy
ito	Special electronic contact tracing application in Germany
km	Kilometer
NHSX/Oxford; COVID Symptom Study, formerly Covid Symptom Tracker; NHSCOVID-19	Special electronic contact tracing application in Great Britain
NZ_COVID_Tracer	Special electronic contact tracking application in New Zealand
Pokemon Go	Special electronic application for centralized contact tracking in Taiwan
PPT	Privacy Proximity Tracking
ProteGOSafe	Special electronic contact tracking application in Poland
Prp.Totl	Percentage of the total variance explained
QR	Easy recognition quick response code
ROBERT	Special electronic contact tracing application in France
Safe Korea	Special electronic application for centralized contact tracing in Korea
SARS-CoV-2	Coronavirus 2 with severe acute respiratory syndrome
Shin Bet	Special electronic application for centralized contact tracing in Israel
Smittestop	Dedicated electronic contact tracking application in Denmark
SMS	"Short Message Service" - technology for receiving and sending short text messages using a cell phone
STATSTICA	Statistical analysis software package
Stay_Home_Safe	Dedicated electronic application for centralized contact tracing in Hong Kong
StopCovid	Special electronic contact tracing application in France
Stopp_Corona	Special electronic contact tracing application in Austria
SwissCovid	Special electronic contact tracing application in Switzerland
TC	Territorial Community
UAH	hryvnya
UTC	United Territorial Community
Var	Variable

WeChat/Alipay	Special electronic application for centralized contact tracing in China
WHO	World Health Organization

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HOW TO CITE THIS ARTICLE

Shcherbak, V.; Gryshchenko, I.; Ganushchak-Yefimenko, L.; Nifatova, O.; Tkachuk V.; Kostiuk T.; Hotra V., (2021). Using a sharing-platform to prevent a new outbreak of COVID-19 pandemic in rural areas. Global J. Environ. Sci. Manage., 7(2): 155-170.

DOI: 10.22034/gjesm.2021.02.01

url: https://www.gjesm.net/article_45801.html