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Trends of the COVID-19 dynamics in 2022 and 2023 vs. the population age, testing and vaccination levels

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Introduction: The population, governments, and researchers show much less interest in the COVID-19 pandemic. However, many questions still need to be answered: why the much less vaccinated African continent has accumulated 15 times less deaths per capita than Europe? or why in 2023 the global value of the case fatality risk is almost twice higher than in 2022 and the UK figure is four times higher than the global one?

Methods: The averaged daily numbers of cases *DCC* and death *DDC* per million, case fatality risks *DDC/DCC* were calculated for 34 countries and regions with the use of John Hopkins University (JHU) datasets. Possible linear and non-linear correlations with the averaged daily numbers of tests per thousand *DTC*, median age of population A, and percentages of vaccinations *VC* and boosters *BC* were investigated.

Results: Strong correlations between age and *DCC* and *DDC* values were revealed. One-year increment in the median age yielded 39.8 increase in *DCC* values and 0.0799 *DDC* increase in 2022 (in 2023 these figures are 5.8 and 0.0263, respectively). With decreasing of testing level *DTC*, the case fatality risk can increase drastically. *DCC* and *DDC* values increase with increasing the percentages of fully vaccinated people and boosters, which definitely increase for greater A. After removing the influence of age, no correlations between vaccinations and *DCC* and *DDC* values were revealed.

Discussion: The presented analysis demonstrates that age is a pivot factor of visible (registered) part of the COVID-19 pandemic dynamics. Much younger Africa has registered less numbers of cases and death per capita due to many unregistered asymptomatic patients. Of great concern is the fact that COVID-19 mortality in 2023 in the UK is still at least 4 times higher than the global value caused by seasonal flu.

KEYWORDS

COVID-19 pandemic dynamics, daily numbers of cases and deaths per capita, case fatality risk, mathematical modeling of infection diseases, statistical methods

Introduction

In the fourth year of the COVID-19 pandemic, the population and governments show much less interest in it. In particular, only 39% of countries reported at least one case to WHO in the period from 31 July to 27 August 2023.[1] Thus accumulated numbers of cases *CC* and deaths *DC* per million show stabilization trends (COVID-19 Data, 2023) and can be used to estimate the impact of different factors on the pandemic dynamics and to answer some important questions. In particular, why the much less vaccinated African continent has accumulated 36 times less cases and 15 times less deaths per capita than Europe (see text footnote 1, COVID-19 Data, 2023, and lines 26 and 27 in Table 1)? Why in 2023 the

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[1] https://covid19.who.int/data. Accessed November 23, 2023.

TABLE 1 Median age, accumulated numbers the COVID-19 cases and deaths per capita in 2021–2023.

No, i	Country or region	Median age in years (see text footnotes 13, 14), A_i	Accumulated numbers of confirmed COVID-19 cases per million (COVID-19 Data, 2023)			Accumulated numbers of COVID-19 related deaths per million (COVID-19 Data, 2023)		
			December 31, 2021, $CC_i^{(1)}$	December 31, 2022, $CC_i^{(2)}$	September 10, 2023, $CC_i^{(3)}$	December 31, 2021, $DC_i^{(1)}$	December 31, 2022, $DC_i^{(2)}$	September 10, 2023, $DC_i^{(3)}$
1	USA	38.5	158,249.8	293,865.4	305,763.9	2,421.163	3,199.789	3,331.912
2	Taiwan	42.3	712.707	370,284.7	428,515.6*	35.575	638.377	795.2*
3	Hong Kong	45.6	1,689.041	350,605	389,150.1**	28.442	1,576.608	1,895.5**
4	India	28.7	24,583.31	31,526.41	31,751.74	339.465	374.479	375.414
5	France	41.7	134,773	587,831.2	603,427.6	1,921.267	2,501.554	2,599.316
6	Germany	47.8	841,31.66	446,707.5	461,051.1	1,411.686	1,987.985	2,098.829
7	Brazil	33.2	103,401.9	168,602.6	175,183.5	2,874.028	3,221.972	3,272.712
8	South Korea	43.2	12,259.77	560,818.7	667,207.1	108.558	622.822	693.495
9	Japan	48.6	13,987.61	234,809.8	272,715.7	148.388	463.995	602.606
10	Italy	46.5	101,315.8	426,312.9	440,207.7	2,324.744	3,130.08	3,242.127
11	UK	40.6	199,110	358,390.2	366,026.1	2,619.105	3,201.28	3,396.691
12	Turkey	32.2	110,635.4	199,255.1	199,255.1	962.067	1,188.394	1,188.394
13	Mexico	29.3	31,644.64	57,030.53	60,217.33	2,382.841	2,599.908	2,623.915
14	Peru	29.1	67,181.25	130,816.2	132,711.8	5,949.676	6,407.655	6,504.19
15	Iran	31.7	69,934.03	85,386.89	85,993	1,485.84	1,633.891	1,652.796
16	Indonesia	31.1	15,472.59	24,391.22	24,730.83	523.025	582.981	587.721
17	Canada	41.8	54,674.47	116,834.2	122,158	779.054	1,268.284	1,382.081
18	South Africa	28.8	57,543.97	67,595.88	67,995.81	1,520.372	1,712.495	1,712.946
19	Egypt	24.1	3,466.327	4,644.856	4,649.271	195.756	223.461	223.714
20	Israel	30.4	146,252.2	491,245.2	511,817.9	874.061	1,235.475	1,340.353
21	Nigeria	18.6	1,105.114	1,219.221	1,311.295	13.865	14.437	14.437
22	Australia	37.5	14,004.71	412,017.8	442,814.2	93.325	680.587	900.471
23	New Zealand	37.2	2,650.961	396,786	458,570.6	9.836	449.541	635.259
24	Vietnam	31.9	17,632.27	117,379.7	118,378.2	329.922	439.835	440.039
25	European Union	44.4	119,091.4	397,673.6	408,494.6	2,033.132	2,668.518	2,763.03

(Continued)

TABLE 1 (Continued)

No, *i*	Country or region	Median age in years (see text footnotes 13, 14), A_i	Accumulated numbers of confirmed COVID-19 cases per million (COVID-19 Data, 2023)			Accumulated numbers of COVID-19 related deaths per million (COVID-19 Data, 2023)		
			December 31, 2021, $CC_i^{(1)}$	December 31, 2022, $CC_i^{(2)}$	September 10, 2023, $CC_i^{(3)}$	December 31, 2021, $DC_i^{(1)}$	December 31, 2022, $DC_i^{(2)}$	September 10, 2023, $DC_i^{(3)}$
26	Europe	42	116,033.4	325,338.4	334,708.4	2,102.787	2,700.244	2,788.427
27	Africa	18	6,904.119	9,111.662	9,201.963	160.421	181.186	181.545
28	Asia	31	17,928.47	58,153.69	63,664.54	266.155	325.065	345.988
29	North America	35	106,779.6	199,059.8	207,318.4	2,040.378	2,580.998	2,670.316
30	South America	31	91,280.98	152,849.9	157,558.3	2,730.093	3,071.714	3,104.744
31	High income countries	No data	107,262	322,668.1	340,229.5	1,632.993	2,214.069	2,320.501
32	Upper middle income countries	No data	33,103.88	89,499.82	96,734.09	871.032	1,016.661	1,055.513
33	Lower middle income countries	No data	19,114.67	28,098.46	28,385.07	345.868	387.735	390.133
34	The world	30.5	35,792.14	91,468.7	96,645.07	686.398	842.509	872.575

*Values calculated with the use of Worldometers (see text footnotes 10, 11).

**Values calculated with the use of Worldometers (see text footnotes 12, 13).

global value of the case fatality risk is almost twice higher than in 2022 and the UK figure is four times higher than the global one (Nesteruk, 2023a)?

We will apply the linear and non-linear correlation analysis using accumulated relative characteristics: the numbers of cases and deaths per million (*CC* and *DC*), numbers of fully vaccinated people and boosters per hundred (*VC* and BC), tests per thousand (*TC*) available in files of John Hopkins University (JHU) (COVID-19 Data, 2023).

The impact of various factors on the COVID-19 pandemic dynamics was estimated in many papers. Some examples can be found in Byass (2020), Davies et al. (2020), Distante et al. (2020), Fanelli and Piazza (2020), Hamzah et al. (2020), Ng and Gui (2020), Chintala et al. (2021), Mohammadi et al. (2021), Nesteruk and Rodionov (2021, 2022a,b), Pardhan and Drydakis (2021), Rossman et al. (2021), Statsenko et al. (2021), Nesteruk (2021a, 2022), Nesteruk et al. (2022), and Nesteruk and Keeling (2023). In particular, *CC* values accumulated as of December 23, 2021 in Ukrainian regions and European countries showed no correlations with the size of population, its density, and the urbanization level, while *DC* and *CFR* = *DC*/*CC* values reduce with the increase of the urbanization level in European countries (Nesteruk et al., 2022). The increase of income (Gross Domestic Product per capita) leads to increase in *CC*, *VC*, *BC*, and *TC* values, but *DC* and *CFR* demonstrate opposite trend in European countries (Nesteruk and Rodionov, 2022b).

Many asymptomatic COVID-19 cases (Shang et al., 2022; Schreiber et al., 2023)[2,3,4] can cause a big difference between visible and real pandemic dynamics (Nesteruk, 2021a,b,c). That is why the higher testing level can increase the numbers of registered cases. Sometimes the testing level is too low to reveal all the cases predicted by theory. Probably such situation occurred in Japan in summer 2022 (Nesteruk, 2023b). It was shown in Nesteruk (2022), that the test per case ratio *TC*/*CC* (or test positivity rate *CC*/*TC*) is very important characteristic to control the pandemic. Very strong correlation between *CC* and *TC* was revealed for values accumulated before August 1, 2022 in European and African countries (Nesteruk and Rodionov, 2022b). Since the *TC* values have stopped to be updated by JHU in different days of 2022 (Nesteruk and Rodionov, 2022b; COVID-19 Data, 2023), in this study, we will investigate a correlation between the averaged daily numbers of cases *DCC* and tests per capita *DTC*.

The severity of SARS-CoV-2 infection increases for older patients (Statsenko et al., 2021); almost half of the infected children can be asymptomatic (Fowlkes et al., 2022). With the use of the statistical analysis of 2020 datasets it was shown that younger populations have less clinical cases per capita and it was predicted that "without effective control measures, regions with relatively older populations could see disproportionally more cases of COVID-19, particularly in the later stages of an unmitigated epidemic" (Davies et al., 2020). This forecast was confirmed in Nesteruk and Keeling (2023) with the use of *CC* and *DC* datasets for 79 countries and regions including 10 so-called Zero-COVID countries.[5] It was shown that 1-year increment in the median age yields 12,000–18,000 increase in *CC* values and 52–83 increase in *DC* values. In this study, we will investigate correlations between median age *A* and the averaged daily numbers of cases and deaths per capita *DCC* and *DDC*, respectively.

The high numbers of circulating SARS-CoV-2 variants[6,7,8] and re-infected persons[9] (Flacco et al., 2022; Guedes et al., 2023) raise questions about the effectiveness of vaccinations. In particular, many scientists are inclined to think that the pandemic will not be stopped only through vaccination (Lazarus et al., 2022). The non-linear correlations show that *CC* and *DC* values increase with the growth of the vaccination level *VC*, while *CFR* decreases (Nesteruk and Rodionov, 2022b). In this study, we will investigate correlations between *VC* and *BC* values registered in 2022 and 2023 and *DCC*, *DDC*, and *CFR* figures. We will try also to answer the question why the number of cases and death per capita are higher in more vaccinated countries.

Materials and methods

We will use the accumulated numbers of laboratory-confirmed COVID-19 cases CC_i and deaths DC_i per million, accumulated numbers of tests per thousand TC_i, accumulated numbers of fully vaccinated people VC_i and boosters BC_i per hundred for 33 countries (shown in Tables 1, 2) and the world ($i = 1, 2, .., 34$). The have chosen the countries with highest numbers of accumulated cases and death [according to the recent WHO reports (see text footnote 1)], some other countries and regions listed in COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) (COVID-19 Data, 2023) (version of file updated on September 28, 2023). Since Chinese statistics shows some contradictions (see, e.g., Nesteruk, 2023c or compare JHU files updated on September 28 and March 9, 2023), we have used only figures for Taiwan and Hong Kong. In particular, in Table 1 we show corresponding CC_i and DC_i values from the March-9-version of JHU file (not available on September 28). The CC_i and DC_i values for Taiwan

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[2] https://edition.cnn.com/2020/11/02/europe/slovakia-mass-coronavirus-test-intl/index.html. Accessed November 23, 2023.

[3] https://www.voanews.com/covid-19-pandemic/slovakias-second-round-coronavirus-tests-draws-large-crowds. Accessed November 23, 2023.

[4] https://podillyanews.com/2020/12/17/u-shkolah-hmelnytskogo-provely-eksperyment-z-testuvannyam-na-covid-19/. Accessed November 23, 2023.

[5] https://en.wikipedia.org/wiki/Zero-COVID. Accessed November 23, 2023.

[6] https://www.who.int/activities/tracking-SARS-CoV-2-variants. Accessed November 30, 2023.

[7] https://en.wikipedia.org/wiki/Variants_of_SARS-CoV-2. Accessed September 13, 2023.

[8] https://www.cdc.gov/coronavirus/2019-ncov/variants/variant-classifications.html. Accessed September 13, 2023.

[9] https://coronavirus.health.ny.gov/covid-19-reinfection-data. Accessed September 13, 2023.

and Hong Kong for 2023 we have calculated with the use of Worldometers.[10,11,12,13] We ignore data from Ukraine and Russia to exclude the influence of military operations on the COVID-19 statistics. To take into account the average age of population, we have used the information about the median ages A_i from Earthly Data[14] and Visual Capitalist[15] (see Table 1).

To calculate the averaged daily numbers of cases DCC and deaths DDC per million in 2022 and 2023 we will use simple formulas:

$$DCC_i^{(j)} = \frac{CC_i^{(j+1)} - CC_i^{(j)}}{T_j}; \quad i = 1, 2, .., 34; \quad j = 1, 2 \tag{1}$$

$$DDC_i^{(j)} = \frac{DC_i^{(j+1)} - DC_i^{(j)}}{T_j}; \quad i = 1, 2, .., 34; \quad j = 1, 2 \tag{2}$$

where T_1 =365 and T_2 =252. The CFR values corresponding to 2022 and 2023 can be calculated as follows:

$$CFR_i^{(j)} = \frac{DC_i^{(j+1)} - DC_i^{(j)}}{CC_i^{(j+1)} - CC_i^{(j)}}; \quad i = 1, 2, .., 34; \quad j = 1, 2 \tag{3}$$

The total average CFR_i^* levels (during the entire period of the COVID-19 pandemic) can be calculated for every country and region:

$$CFR_i^* = \frac{DC_i^{(3)}}{CC_i^{(3)}}; \quad i = 1, 2, .., 34 \tag{4}$$

To estimate the average daily numbers of tests per thousand, we will use the formula:

$$DTC_i^{(j)} = \frac{TC_i^{(2)} - TC_i^{(1)}}{T_i^{(TC)}}; \quad i = 1, 2, .., 34 \tag{5}$$

Durations of corresponding periods of time $T_i^{(TC)}$ are listed in Table 2. Unfortunately, the testing data is not available for many countries and regions.

We will use the linear regression to calculate the regression coefficients r and the optimal values of parameters a and b for corresponding best fitting straight lines (Draper and Smith, 1998):

$$y = a + bx \tag{6}$$

where explanatory variables x will be A, DTC, VC, and BC and dependent variables y will be DCC, DDC, CFR, DTC, VC, and BC.

We will use also the F-test for the null hypothesis that says that the proposed linear relationship (6) fits the data sets. The experimental values of the Fisher function can be calculated using the formula:

$$F = \frac{r^2(n-m)}{(1-r^2)(m-1)} \tag{7}$$

where n is the number of observations (number of countries and regions taken for statistical analysis); m=2 is the number of parameters in the regression equation (Draper and Smith, 1998). The corresponding experimental values F have to be compared with the critical values $F_C(k_1, k_2)$ of the Fisher function at a desired significance or confidence level ($k_1 = m - 1$, $k_2 = n - m$, see, e.g., Appendix[16]). If $F/F_C(k_1, k_2) < 1$, the correlation is not supported by the results of observations. The highest values of $F/F_C(k_1, k_2)$ correspond to the most reliable correlation.

We will use also non-linear regression:

$$y = cx^{\gamma} \tag{8}$$

which can be reduced to the linear one by introducing new variables (Nesteruk and Rodionov, 2022b):

$$z \equiv \log y = \log c + \gamma w, \quad w \equiv \log x \tag{9}$$

Unfortunately, the testing data are almost not available in 2023, since the population and governments show much less interest in the COVID-19 pandemic. This fact and scattered dates of fixing the VC and BC values (see Table 2) complicate a full-fledged statistical analysis.

Results

The results of calculations with the use of Equations (1–5) are listed in Table 3 and shown in Figures 1–3 vs. median age, testing level DTC, percentage of fully vaccinated persons $VC_i^{(1)}$ (for 2022) and $VC_i^{(2)}$(for 2023), and numbers of boosters per hundred $BC_i^{(1)}$ (for 2022) and$BC_i^{(2)}$ (for 2023). The averaged daily numbers of cases decreased drastically in 2023 in comparison with corresponding values in 2022 (compare $DCC^{(2)}$ and $DCC^{(1)}$ values in Table 3 or "triangles" and "circles" in Figure 1, the only exception is Nigeria). The global figure of average daily cases has diminished 7.4 times in 2023 (see the last row of Table 3). Turkey has stopped to show new cases in 2023. USA, China, Japan do not report any COVID-19 cases and related deaths since May 15, 2023 (see text footnote 1).

In 2023 the averaged daily numbers of deaths significantly decreased in all countries and regions (compare $DDC^{(2)}$ and $DDC^{(1)}$ values in Table 3 or "triangles" and "circles" in Figure 2), yielding 3.6 times decrease in global DDC figures (see the last row of

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[10] https://www.worldometers.info/coronavirus/country/taiwan/. Accessed September 30, 2023.

[11] https://www.worldometers.info/world-population/taiwan-population/. Accessed September 30, 2023.

[12] https://www.worldometers.info/world-population/china-hong-kong-sar-population/. Accessed September 30, 2023.

[13] https://www.worldometers.info/coronavirus/country/china-hong-kong-sar/. Accessed September 30, 2023.

[14] https://database.earth/population. Accessed September 30, 2023.

[15] https://www.visualcapitalist.com/mapped-the-median-age-of-every-continent/. Accessed September 30, 2023.

[16] https://onlinepubs.trb.org/onlinepubs/nchrp/cd-22/manual/v2appendixc.pdf. Accessed November 23, 2023.

TABLE 2 Accumulated numbers the tests per capita and percentage of fully vaccinated people and boosters in 2021-2023 (COVID-19 Data, 2023).

No, i	Country or region	Accumulated numbers of tests per thousand $TC_i^{(j)}$, corresponding dates and number of days $T_i^{(TC)}$					Numbers of fully vaccinated people per hundred as of:		Numbers of boosters per hundred as of:	
		$TC_i^{(1)}$	Date in 2021	$TC_i^{(2)}$	Date in 2022	$T_i^{(TC)}$, days	July 1. 2022 $VC_i^{(1)}$	July 1. 2023 $VC_i^{(2)}$	July 1. 2022 $BC_i^{(1)}$	July 1. 2023 $BC_i^{(2)}$
1	USA	2,155.384	Dec 31	2,708.533	Jun 18	169	67.33	69.47[23]	37.91	40.08[8]
2	Taiwan	208.248	Dec 31	545.749	Jun 22	173	81.52	87	72.89	106.4
3	Hong Kong	4,615.889	Dec 31	6,594.993	May 24	144	86.21	90.81	60.36	94.91
4	India	481.597	Dec 31	609.938	Jun 21	172	64.58	67.17	3.15	16.04
5	France	2,908.831	Dec 31	4,126.754	Jun 18	169	78.14	78.44	58.86	70.34
6	Germany	1,108.669	Dec 26	1,574.021	Jun 12	168	76.04	76.24[20]	68.6	77.72[20]
7	Brazil	308.411	Dec 31	330.912	March 11	70	78.52	81.82[17]	49.7	58.7[17]
8	South Korea	874.47	Dec 31	1,934.578	Jun 15	166	85.48	85.64[25]	73.01	79.76[14]
9	Japan	224.641	Dec 31	429.37	Jun 22	173	82.6	83.4[22]	64.04	141.72[22]
10	Italy	2,365.578	Dec 31	3,795.998	Jun 22	173	81.14	81.22	69.66	80.88
11	UK	5,845.841	Dec 31	7,480.121	May 19	139	74.36	75.19[10]	59.26	59.81[9]
12	Turkey	1,403.53	Dec 31	1,924.668	May 31	151	62.21[6]	62.31[13]	43.22[6]	48.54[13]
13	Mexico	95.052	Dec 31	122.879	Jun 18	169	62.7[3]	64.19[11]	41.65[3]	44.73[12]
14	Peru	646.299	Dec 31	859.283	April 05	95	81.44	84.21	61.41	90.41
15	Iran	477.494	Dec 31	594.485	Jun 01	152	65.34[2]	66.15[29]	31.11[2]	32.27[29]
16	Indonesia	155.199	Dec 31	217.363	March 21	80	61.18[30]	63.48[27]	17.86[30]	24.99[27]
17	Canada	1,380.218	Dec 31	1,629.606	Jun 06	157	81.79	82.6[15]	57.41	79.14[15]
18	South Africa	357.471	Dec 31	431.667	Jun 22	173	31.83	35.13[26]	5.79	7.36[26]
19	Egypt	No data		109.415	May 01		33.6[5]	38.15[24]	5.03[5]	13.71[24]
20	Israel	3,637.259	Dec 31	5,573.137	Jun 22	173	65.09	65.19[21]	56.45	61.03[21]
21	Nigeria	17.916	Dec 26	24.74	Jun 22	178	9.6[4]	31.94[16]	0.54[4]	5.63[16]
22	Australia	2,120.241	Dec 31	2,830.525	Jun 22	173	82.7[3]	82.7[18]	62.19	75.6[15]
23	New Zealand	1,087.221	Dec 31	1,416.09	Jun 23	174	79.34	80.66[19]	52.95	68.81[19]
24	Vietnam	765.759	Dec 30	880.538	Jun 20	172	81.67[7]	87.55[28]	57.03[1]	59.05[28]

(Continued)

TABLE 2 (Continued)

No, i	Country or region	Accumulated numbers of tests per thousand $TC_i^{(j)}$, corresponding dates and number of days $T_i^{(TC)}$					Numbers of fully vaccinated people per hundred as of:		Numbers of boosters per hundred as of:	
		$TC_i^{(1)}$	Date in 2021	$TC_i^{(2)}$	Date in 2022	$T_i^{(TC)}$, days	July 1. 2022 $VC_i^{(1)}$	July 1. 2023 $VC_i^{(2)}$	July 1. 2022 $BC_i^{(1)}$	July 1. 2023 $BC_i^{(2)}$
25	European Union	No data		No data			72.56	72.86	52.15	62.09
26	Europe	No data		No data			65.26	66.21	40.44	48.22
27	Africa	No data		No data			17.89	31.36	2.1	6.4
28	Asia	No data		No data			70.16	73.22	28.35	38.23
29	North America	No data		No data			63.72	65.7	37.23	41.9
30	South America	No data		No data			74.75	77.12	47.5	58.31
31	High income countries	No data		No data			73.18	74.3	51.83	66.37
32	Upper middle income countries	No data		No data			77.15	78.74	45.55	49.97
33	Lower middle income countries	No data		No data			53.28	59.36	9.17	19.35
34	The world	No data		No data			60.07	64.66	26.58	34.93

Figures corresponding to different days in 2022:
May: ^{1}—18.
June: ^{2}—1; ^{3}—17; ^{4}—19; ^{5}—29; ^{6}—30; ^{30}—21.
July: ^{7}—7.
September: ^{8}—1; ^{9}—4; ^{10}—11.
October: ^{11}—7.
November: ^{12}—18; ^{13}—22.
December: ^{14}—12.
Figures corresponding to different days in 2023:
February: ^{15}—2.
March: ^{16}—19; ^{17}—22; ^{18}—24.
April: ^{19}—4; ^{20}—7.
May: ^{21}—4; ^{22}—7; ^{23}—9; ^{24}—21; ^{25}—26.
June: ^{26}—4; ^{27}—6; ^{28}—30.
July: ^{29}—4.

TABLE 3 The results of calculations of average daily characteristics with the use of Equations (1–4).

No, i	Country or region	Average daily numbers of COVID-19 cases per million, $DCC^{(j)}$		Average daily numbers of deaths per million, $DDC^{(j)}$		Case fatality risks			Average daily numbers of tests per thousand, DTC_i
		2022	2023	2022	2023	2022, $CFR^{(1)}$	2023, $CFR^{(2)}$	Total, CFR^{*}, Equation (4)	
1	USA	371.55	47.22	2.1332	0.5243	0.00574	0.0111	0.0109	3.27
2	Taiwan	1,012.53	231.08	1.6515	0.6223	0.00163	0.00269	0.00186	1.95
3	Hong Kong	955.93	152.96	4.2416	1.2654	0.00444	0.00827	0.00487	13.74
4	India	19.02	0.89	0.0959	0.00371	0.00504	0.00415	0.0118	0.75
5	France	1,241.26	61.89	1.5898	0.3879	0.00128	0.00627	0.00431	7.21
6	Germany	993.35	56.92	1.5789	0.4399	0.00159	0.00772	0.00455	2.77
7	Brazil	178.63	26.11	0.9533	0.2013	0.00534	0.00771	0.0187	0.32
8	South Korea	1,502.90	422.18	1.4089	0.2804	0.000937	0.000664	0.00104	6.39
9	Japan	604.99	150.42	0.8647	0.5500	0.00142	0.00365	0.00221	1.18
10	Italy	890.40	55.14	2.2064	0.4446	0.00248	0.00806	0.00736	8.27
11	UK	436.38	30.30	1.5950	0.7754	0.00366	0.02559	0.00928	11.76
12	Turkey	242.79	0	0.6201	0	0.00255	–	0.00596	3.45
13	Mexico	69.55	12.65	0.5947	0.09527	0.00855	0.00753	0.0436	0.16
14	Peru	174.34	7.52	1.2547	0.3831	0.00720	0.05093	0.0490	2.24
15	Iran	42.34	2.41	0.4056	0.07502	0.00958	0.03119	0.0192	0.77
16	Indonesia	24.43	1.35	0.1643	0.01881	0.00672	0.01396	0.0238	0.78
17	Canada	170.30	21.13	1.3404	0.4516	0.00787	0.02138	0.0113	1.59
18	South Africa	27.53	1.59	0.5264	0.00179	0.01911	0.00113	0.0252	0.43
19	Egypt	3.22	0.0175	0.0759	0.001004	0.02351	0.05730	0.0481	–
20	Israel	945.19	81.64	0.9902	0.4161	0.00105	0.00510	0.00262	11.19
21	Nigeria	0.31	0.365	0.001567	0	0.00501	0	0.0110	0.0383
22	Australia	1,090.44	122.21	1.6089	0.8726	0.00148	0.00713	0.00203	4.11
23	New Zealand	1,079.82	245.18	1.2047	0.7370	0.00112	0.00301	0.00139	1.89
24	Vietnam	273.28	3.96	0.3011	0.0008095	0.00110	0.000204	0.00371	0.67
25	European Union	763.24	42.94	1.7408	0.3750	0.00228	0.00873	0.00676	–

(Continued)

Table 3). Seasonal global influenza mortality is between 294 and 518 thousand in the period from 2002 to 2011 (Paget et al., 2019). After dividing the presented figures over the world population 8,060.5 million (see text footnote 14) and 365 days, the corresponding averaged daily number of deaths per million $DDC_{(infl)}$ will range between 0.1 and 0.18. The global value of $DDC_{34}^{(2)} = 0.1193$ is comparable with the influenza mortality, but in 2023 in many countries (including the UK) the corresponding $DDC^{(2)}$ values are much higher than $DDC_{(infl)}$ (see Table 3).

The global case fatality risk in 2023 is approximately twice higher than in 2022 despite of the increase in percentages of fully vaccinated people and boosters (see the last rows of Tables 2, 3). In 2023 the *CFR* values were lower only in India, South Korea, Mexico, South Africa, Nigeria, Vietnam and Africa (compare corresponding columns in Table 3). There are countries with drastic growth of the *CFR* values in 2023 in comparison with 2022 (for example, almost seven times for the UK and Peru). In 2023 only Egypt, Peru and Iran have higher case fatality risks than in the UK (see Table 3; the markers corresponding to the UK are placed inside red circles in Figures 1–3).

There are countries with traditional high levels of *CFR*. To smooth temporarily fluctuations, the total average CFR_i^* values (during the entire period of the COVID-19 pandemic) were calculated with the use of Equation (4), listed in Table 3 and shown in Figure 3 by blue "stars." The value CFR_{11}^* corresponding to the UK is only slightly higher than the global one. Many countries (e.g., the US, India, Mexico, Peru, Iran, Indonesia, Canada, South Africa, Egypt, Nigeria) have higher CFR_i^* values.

To remove the influence of the seasonal factors in the UK, let us calculate the values of $DCC_{11}^{(1*)}$, $DDC_{11}^{(1*)}$ and $CFR_{11}^{(1*)}$ for the period January 1, 2022–May 19, 2022 and the same values $DCC_{11}^{(2*)}$, $DDC_{11}^{(2*)}$ and $CFR_{11}^{(2*)}$ and for the period January 1, 2023–May 19, 2023 with the use of Equations (1–3) and JHU datasets:

$$DCC_{11}^{(1*)} = (329{,}252.5–199{,}110)/139 = 936.28;$$
$$DDC_{11}^{(1*)} = (2{,}944.618–2{,}619.105)/139 = 2.34;$$
$$CFR_{11}^{(1*)} = (2{,}944.618–2{,}619.105)/(329{,}252.5–199{,}110) = 0.0025;$$
$$DCC_{11}^{(2*)} = (364{,}587.9–358{,}390.2)/139 = 44.59;$$
$$DDC_{11}^{(2*)} = (3{,}370.043–3{,}201.28)/139 = 1.214;$$
$$CFR_{11}^{(2*)} = (3{,}370.043–3{,}201.28)/(364{,}587.9–358{,}390.2) = 0.0272.$$

In 2023 we can see huge decrease in the number of cases and moderate diminishing in the number of death. As the result, the case fatality risk in the beginning of 2023 exceeded the 2022 figure around 11 times. The reason could be explained by the fact that testing and reporting most cases we stopped in UK since April 2022. The only people who get recorded as cases are those that are tested in hospital, and even there not everyone with respiratory infections gets tested. The death data may include all those where COVID-19 is listed on the death certificate, which might even include those that have not tested positive but where the doctors suspect COVID-19.

TABLE 3 (Continued)

No, i	Country or region	Average daily numbers of COVID-19 cases per million, $DCC^{(j)}$		Average daily numbers of deaths per million, $DDC^{(j)}$		Case fatality risks			Average daily numbers of tests per thousand, DTC_i
		2022	2023	2022	2023	2022, $CFR^{(1)}$	2023, $CFR^{(2)}$	Total, CFR^*, Equation (4)	
26	Europe	573.43	37.18	1.6369	0.3499	0.00285	0.00941	0.00833	–
27	Africa	6.05	0.358	0.05689	0.001425	0.00941	0.00398	0.0197	–
28	Asia	110.21	21.86	0.1613	0.08303	0.00146	0.00380	0.00543	–
29	North America	252.82	32.77	1.4811	0.3544	0.00586	0.01082	0.0129	–
30	South America	168.68	18.68	0.9360	0.1311	0.00555	0.00702	0.0197	–
31	High income countries	590.15	69.68	1.5920	0.4223	0.00270	0.00606	0.00682	–
32	Upper middle income countries	154.51	28.71	0.3990	0.1541	0.00258	0.00537	0.0109	–
33	Lower middle income countries	24.61	1.14	0.1147	0.009516	0.00466	0.00837	0.0137	–
34	The world	152.54	20.54	0.4277	0.1193	0.00280	0.00581	0.00903	–

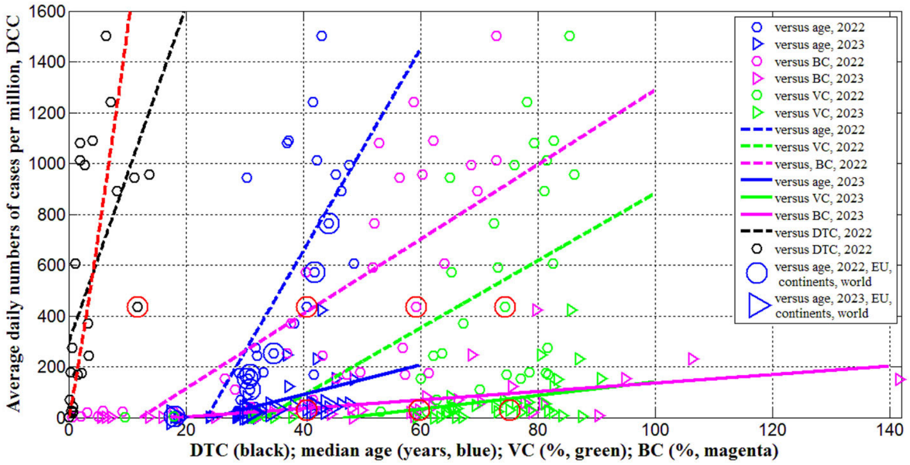

FIGURE 1
Averaged daily numbers of COVID-19 cases per million in 2022 ("circles") and 2023 ("triangles") vs. median age (blue) and levels of vaccinations (green), boosters (magenta) and testing (black). Best fitting lines are solid for 2023 and dashed for 2022. The UK data are located in red circles. The values corresponding to EU, continents and the world are duplicated by lager markers. Red curve represents the results of non-linear correlation (Equation 10).

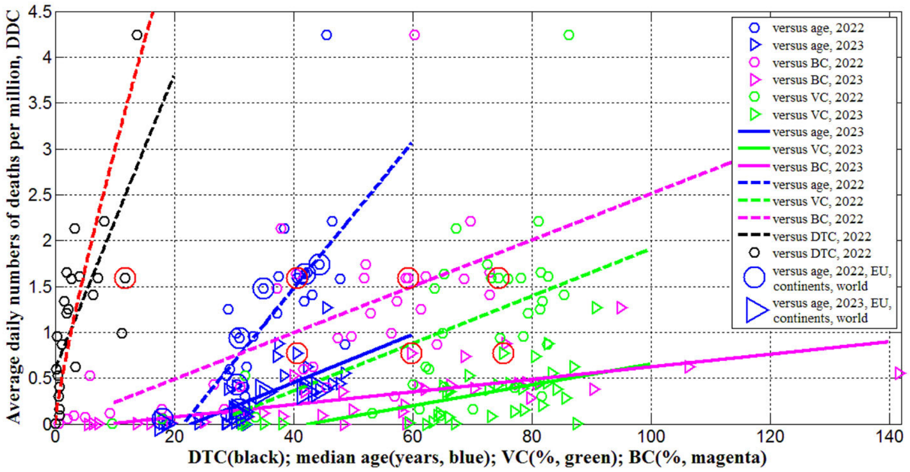

FIGURE 2
Averaged daily numbers of COVID-19 related deaths per million in 2022 ("circles") and 2023 ("triangles") vs. median age (blue) and levels of vaccinations (green), boosters (magenta) and testing (black). Best fitting lines are solid for 2023 and dashed for 2022. The UK data are located in red circles. The values corresponding to EU, continents and the world are duplicated by lager markers. Red curve represents the results of non-linear correlation (Equation 11).

It must be noted, the growth of *CFR* in the UK occurred in the period of increasing the vaccination and booster levels (COVID-19 Data, 2023):

	VC	BC
December 31, 2021	70.26%	50.5%
May 19, 2022	73.92%	58.67%
September 11, 2022	79.71%	75.19%

To investigate possible correlations between *DCC, DDC* and *CFR* values and explanatory variables *A, DTC*, $VC^{(1)}$, $VC^{(2)}$, $BC^{(1)}$, and $BC^{(2)}$, the linear regression (Equation 6) and Fisher test were used. The results of calculations of optimal values of parameters *a* and *b*, correlation coefficients and experimental values of the Fisher function *F* (Equation 7) are listed in Table 4. The *F* values were compared with the critical ones $F_C(1, n-2)$ at the confidence level 0.01. The numbers of observations *n* are different for different correlations due to the absence of data for some countries and regions.

Since many COVID-19 patients are asymptomatic (see text footnotes 2–4) (Nesteruk, 2021b,c, 2023b; Fowlkes et al., 2022), the high testing level (*DTC* or *TC*) could help to reveal more cases and COVID-19 related deaths. This trend was supported statistically (see rows 4 and 11 in Table 4 and black lines in Figures 1, 2). Nevertheless, the linear regression yields unacceptable non-zero values of parameter *a*, which mean that some cases and deaths could be revealed at zero testing level. To remove this discrepancy,

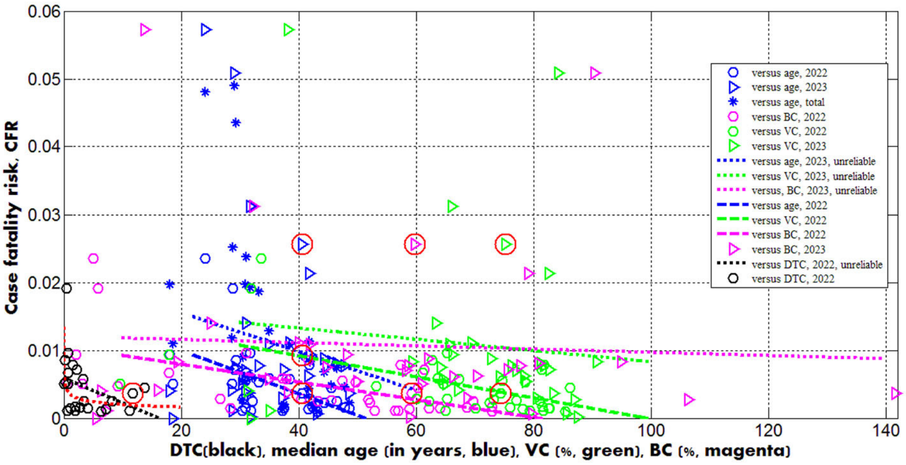

FIGURE 3
Case fatality risks in 2022 ("circles") and 2023 ("triangles") vs. median age (blue) and levels of vaccinations (green), boosters (magenta) and testing (black). Best fitting lines are solid for 2023 and dashed for 2022. The dotted lines correspond to the correlations that are not supported at the significance level 0.01. The UK data are located in red circles. Red curve represents the results of non-linear correlation (Equation 12).

the non-linear approach (Equations 8, 9) was applied for the same countries listed in Table 3 ($n = 23$).

Equations (10–12) represent the best fitting curves (see red lines in Figures 1–3), correlation coefficients and experimental values of the Fisher function:

$$DCC^{(1)} = 118.7499 \cdot \mathrm{DTC}^{1.106479}; r = 0.81835; F = 42.58 \quad (10)$$

$$DDC^{(1)} = 0.4428336 \cdot \mathrm{DTC}^{0.828329}; r = 0.76624; F = 29.86 \quad (11)$$

$$CFR^{(1)} = \frac{0.00372913}{\mathrm{DTC}^{0.27815}}; \; r = -0.46942; \;\; F = 5.94 \quad (12)$$

The values of r^2 and F for variables z and w are higher than for y and x [compare corresponding values in Equations (10–12) and rows 4, 11, and 18 in Table 4]. The relationships (10) and (11) are supported at significance level 0.001 $F_C(1, 21) = 14.6[F_C(1, 21) = 14.6]$. The similar very strong correlation between the numbers of cases and tests per capita accumulated in European and African countries as of August 1, 2022 was found in Nesteruk and Rodionov (2022b):

$$CC = 80.099 \cdot \mathrm{TC}^{1.02755}; \; n = 89; \; r = 0.9496; \; F = 767.6 \quad (13)$$

Nevertheless, 16 European countries with the highest testing level ($TC > 3{,}000$) have demonstrated no correlation between CC and TC even at the significance level 0.05 (Nesteruk and Rodionov, 2022b).

Only 5 countries and territories listed in Table 2 (Hong Kong, France, Italy, the UK, and Israel) had TC values higher than 3,000 in 2022. The $DCC^{(1)}$ values are rather high and vary from 436 to 1,241 in these countries (see Table 3). Nevertheless, many infectious persons were not detected. This is evidenced not only by the higher numbers of cases per capita in South Korea ($DCC_8^{(1)}$= 1,502.9, Table 3) at lower testing level (compare corresponding DTC values in Table 3), but also by the results of total testing in some countries and institutions, which revealed many previously unregistered COVID-19 patients (see text footnotes 2–4). Taking the maximum $DCC_8^{(j)}$ values (corresponding to South Korea) as estimations real number of cases per capita in 2022 and 2023, we can calculate the visibility coefficients

$$\beta_i^{(j)} = \frac{\mathrm{DCC}_8^{(j)}}{\mathrm{DCC}_i^{(j)}}; \; j = 1, 2; \; i = 1, 2, ..., 34 \quad (14)$$

as the ratios of real and registered numbers of cases [similar relationship can be obtained using the accumulated numbers of cases per capita (Nesteruk and Rodionov, 2022b)]. For example, figures corresponding to the UK are$\beta_{11}^{(1)} = 3.4$; $\beta_{11}^{(2)} = 13.9$; Europe—$\beta_{26}^{(1)} = 2.6$; $\beta_{26}^{(2)} = 11.4$, and Africa—$\beta_{27}^{(1)} = 248.4$; $\beta_{27}^{(2)} = 1{,}179.3$.

An experimental estimation of the visibility coefficient can be obtained from the results of total testing in Slovakia [89.5% of population was tested on October 31–November 7, 2020 and a number of previously undetected cases, equal to about 1.63% of the population was revealed (see text footnotes 2, 3)]. Since the number of detected cases in Slovakia was approximately 1% of population (COVID-19 Data, 2023), we can estimate the visibility coefficient $\beta \approx 2.63$ for that period. As of September 10, 2023 the ratio of CC values for South Korea and Slovakia [667,207.1/330,868.413 (COVID-19 Data, 2023)] yields the visibility coefficient 2.02. The results of a random testing in two kindergartens and two schools in Chmelnytskii (Ukraine) revealed the value of visibility coefficient 3.9 in December 2020 (see text footnote 4).

The generalized SIR models and algorithms of their parameter identification (Nesteruk, 2021b,d, 2023b) allowed theoretical estimating of the visibility coefficients. In particular, values from 3.7 to 20.4 were obtained for Ukraine (Nesteruk, 2021a,b) and 5.4 for Qatar (Nesteruk, 2021c) in different periods of the COVID-19 pandemic. The lack of appropriate testing did not allowed detecting the first SARS-CoV-2 cases, which probably appeared long before December 2019 (Weinberger et al., 2020). In particular, theoretical

TABLE 4 Optimal values of parameters in Equation (1), correlation coefficients and the results of Fisher test applications.

Number	Variable x	Number of observations n	Correlation coefficient R	Optimal values of parameter a in Equation (6)	Optimal values of parameter b in Equation (6)	Experimental value of the Fisher function F, Equation (7), $m = 2$	Critical value of Fisher function $F_c(1,n\text{-}2)$ for the confidence level 0.01 (Appendix[16])	F/F_c
Correlations for the averaged daily numbers of COVID-19 cases in 2022, $DCC^{(1)}$								
1	Versus age	31	0.7108	−937.43	39.767	29.616	7.77	3.81
2	Versus $VC^{(1)}$	34	0.56202	−444.10	13.252	14.775	7.74	1.91
3	Versus $BC^{(1)}$	34	0.7459	−181.28	14.687	40.136	7.74	5.19
4	Versus DTC	23	0.5613	292.96	66.052	9.66	7.85	1.2
Correlations for the averaged daily numbers of COVID-19 cases in 2023, $DCC^{(2)}$								
5	Versus age	31	0.5009	−143.583	5.8231	9.711	7.77	1.25
6	Versus $VC^{(2)}$	34	0.4696	−128.811	2.6796	9.051	7.74	1.17
7	Versus $BC^{(2)}$	34	0.5674	−32.3957	1.6692	15.195	7.74	1.96
Correlations for the averaged daily numbers of deaths in 2022, $DDC^{(1)}$								
8	Versus age	31	0.7324	−1.7244	0.07993	33.553	7.77	4.32
9	Versus $VC^{(1)}$	34	0.5553	−0.6756	0.02582	14.264	7.74	1.84
10	Versus $BC^{(1)}$	34	0.6513	−0.02176	0.02529	23.579	7.74	3.05
11	Versus DTC	23	0.7138	0.59477	0.16076	21.8	7.85	2.8
Correlations for the averaged daily numbers of deaths in 2023, $DDC^{(2)}$								
12	Versus age	31	0.6793	−0.6040	0.02626	24.843	7.77	3.20
13	Versus $VC^{(2)}$	34	0.5927	−0.4892	0.0114	17.332	7.74	2.24
14	Versus $BC^{(2)}$	34	0.6903	−0.06489	0.006845	29.131	7.74	3.76
Correlations for the case fatality risks in 2022, $CFR^{(1)}$								
15	Versus age	31	−0.5006	0.01631	−0.0003177	9.698	7.77	1.25
16	Versus $VC^{(1)}$	34	−0.5901	0.01538	−0.0001553	17.092	7.74	2.21
17	Versus $BC^{(1)}$	34	−0.5937	0.01053	−0.0001305	17.423	7.74	2.25
18	Versus DTC	23	−0.3566	0.005909	−0.00036525	3.059	7.85	0.39
Correlations for the case fatality risks in 2023, $CFR^{(2)}$								
19	Versus age	30	−0.1700	0.02122	−0.00028515	0.834	7.78	0.11
20	Versus $VC^{(2)}$	33	−0.1008	0.01656	−8.2800e−05	0.318	7.75	0.041
21	Versus $BC^{(2)}$	33	−0.0560	0.01203	−2.36499e−05	0.0975	7.75	0.013

estimates give the date of the appearance of the first case at the beginning of August 2019 (Nesteruk, 2021d).

Dependence (12) can be accepted at significance level 0.05 [$F_C(1,21) = 4.43$; a similar equation can be obtained by dividing (11) over (10)] and shows that the case fatality risk increases with diminishing of the testing level even in the period of the high interest in the SARS-CoV-2 infection (as it was in 2022). In 2023, when the people paid attention to severe cases only and make tests correspondingly, CFR values can increase drastically. Therefore, one should probably not be afraid of a significant increase of the case fatality risk in the UK in 2023. Of much greater concern is the fact that COVID-19 mortality in this country ($DDC_{11}^{(2)} = 0.7754$, see Table 3) is still at least 4 times higher than the global value caused by seasonal flu (Paget et al., 2019).

Equations (10, 13) may give the illusion that the low number of cases per capita in Africa is due only to the low testing level typical for low-income countries (see Nesteruk and Rodionov, 2022b). The visibility coefficients and another characteristic—the ratio of the number of tests to the number of cases DTS—will allow us to understand the situation and draw the right conclusions. High DTS values mean that many persons surrounding the detected infectious patient (e.g., family members, colleagues, neighbors) were tested and isolated (this causes a decrease in the number of new infections, i.e., DCC). For example, very high tests per case ratios ($DTS > 100$) in Hong Kong in 2020 and 2021 allowed controlling the COVID-19 epidemic completely (Nesteruk, 2022) [the smoothed daily numbers of new cases per million did not exceed 20 (COVID-19 Data, 2023)]. After January 18, 2022, the daily numbers of new cases started to increase, but the daily numbers of tests remained almost constant yielding drastically diminishing of the daily tests per case ratio (Nesteruk, 2022) and very high DCC values in February-March 2022 (COVID-19 Data, 2023).

It follows from Equation (10) that the averaged daily test per case ratio:

$$DTS \equiv \frac{1000 \cdot DTC}{DCC^{(1)}} = \frac{13.34}{\left[DCC^{(1)}\right]^{0.0962}}$$

increases for countries with low DCC figures (in particular, for African ones, see Table 3). The similar relationship follows from Equation (13) for the accumulated characteristic $TS = 1{,}000^{*}TC/CC$. For example, DTS values (calculated using the information available in Table 3) are equal to 26.9 (the UK); 39.4 (India); 123.5 (Nigeria); 4.3 (South Korea); 1.95 (Japan) and demonstrate that the probability to miss an infectious person due to the lack of tests is much higher in Japan or South Korea than in Nigeria or India. During the severe pandemic wave in Japan in summer 2022, the daily numbers tests probably were not enough to confirm COVID-19 in patients with symptoms (Nesteruk, 2023b).

Therefore, the reason for the low number of registered cases per capita in Africa or in India should not be found in insufficient testing, but in large values of the visibility coefficients (Equation 14), which attribute to large numbers of asymptomatic infections. Since the severity of SARS-CoV-2 infection increases for older patients (Davies et al., 2020; Statsenko et al., 2021) and almost half of the infected children can be asymptomatic (Fowlkes et al., 2022), the regions with older population are expected to have much higher accumulated numbers of cases per capita (Davies et al., 2020). It was shown that 1-year increment in the median age yields 12,000–18,000 increase in CC values (Nesteruk and Keeling, 2023). Rows 1 and 5 in Table 4 and blue lines in Figure 1 illustrate the same trend for DCC values. One-year increment in the median age increased DCC values by 39.8 in 2022 and by 5.8 in 2023.

The stronger correlations and same trends were obtained for the averaged daily numbers of deaths per capita DDC vs. median age of population A (see rows 8 and 12 in Table 4 and blue lines in Figure 2). One-year increment in the median age increases the DDC values by 0.0799 in 2022 and by 0.0263 in 2023. The characteristics calculated for large regions (EU, continents and the world) are very close to the best fitting blue lines (see large markers in Figures 1, 2). We can conclude that the young age of Africa ($A_{27} = 18$, see Table 1) is the main reason of very low numbers of cases and death per capita registered on this continent.

Opposite and much weaker age trends we can see for the case fatality risks (lines 15 and 19 in Table 4). The decrease of CFR values with increase of the age (supported only by the 2022 dataset) looks unexpected [especially taking into account the fact that in 2020 younger populations had less clinical cases per capita (Davies et al., 2020)]. Probably, the reason is better medical treatment in the reach countries with the high median age.

The numbers of cases and deaths per capita increase with increasing the percentages of fully vaccinated people and boosters (see rows 2, 3, 6, 7, 9, 10, 13, 14 in Table 4 and green and magenta best fitting lines in Figures 1, 2). Re-infections in vaccinated persons are common (Flacco et al., 2022; Guedes et al., 2023), but a very clear uprising trend with increasing VC and BC values is unexpected despite the similar result for smoothed daily numbers of cases reported in Nesteruk and Rodionov (2022a) (JHU datasets with 7-days-smoothing corresponding to September 1, 2021 and February 1, 2023 were used for statistical analysis). Obtained trends could be a result of age influence, since the most vaccinated countries have higher A_i values (see Tables 1, 2). We will discuss this correlation in the next Section. Another reason could be the introduction of special passports that removed restrictions for vaccinated persons. Many vaccinated people in countries with high VC and BC values started to visit crowded places, travel despite they can spread the infection. In many countries (in particular, in Ukraine) the vaccination procedure was associated with overcrowding in hospitals, which could contribute to the spread of the infection too.

As expected, the case fatality risks decrease with increasing the percentages of fully vaccinated people and boosters (see rows 16, 17, 20, 21 in Table 4 and green and magenta best fitting lines in Figure 3). Similar result was obtained in Nesteruk and Rodionov (2022a) with the use of JHU datasets for European and some other countries. In 2023, the decreasing trend was not supported by Fisher test. Probably, this is due to the more chaotic data. In particular, the different days correspond to $VC_i^{(2)}$ and $BC_i^{(2)}$ values listed in Table 2, no CFR value can be calculated for Turkey.

Discussion

The explanatory variables A, DTC, $VC^{(1)}$, $VC^{(2)}$, $BC^{(1)}$, and $BC^{(2)}$, used in our analysis can be also dependent on each other. We have used the linear regression (Equation 6) and Fisher test to find correlations between DTC, $VC^{(1)}$, $VC^{(2)}$, $BC^{(1)}$, and $BC^{(2)}$ values and explanatory variable A. The results of calculations are listed in

TABLE 5 Correlations vs. the median age of populations and purified levels of vaccinations.

Number	Variable *y*	Number of observations *n*	Correlation coefficient *R*	Optimal values of parameter *a* in Equation (1)	Optimal values of parameter *b* in Equation (1)	Experimental value of the Fisher function *F*, Equation (3), $m = 2$	Critical value of Fisher function $F_c(1,n\text{-}2)$ for the confidence level 0.01 (Appendix[16])	F/F_c
Correlations vs. median age of population, *A*								
1	*DTC*	23	0.4389	−4.7762	0.23290	5.011	7.85	0.64
2	$VC^{(1)}$	31	0.7673	2.3288	1.83706	41.515	7.77	5.34
3	$VC^{(2)}$	31	0.7348	17.5274	1.49084	34.036	7.77	4.38
4	$BC^{(1)}$	31	0.7933	−34.8469	2.21980	49.246	7.77	6.34
5	$BC^{(2)}$	31	0.7810	−51.3696	3.03961	45.339	7.77	5.84
Correlations vs. “purified” numbers of fully vaccinated persons per hundred, VP								
6	$DCC^{(1)}$	31	0.03726	463.8161	1.35771	0.0403	7.77	0.0052
7	$DDC^{(1)}$	31	0.00318	1.0919	0.00022628	0.000294	7.77	3.8e-5
8	$CFR^{(1)}$	31	−0.3236	0.005114	−0.00013372	3.391	7.77	0.43
Correlations vs. “purified” numbers of boosters per hundred, BP								
9	$DCC^{(1)}$	31	0.2969	463.792	9.75216	2.804	7.77	0.36
10	$DDC^{(1)}$	31	0.0989	1.0919	0.0063360	0.2864	7.77	0.037
11	$CFR^{(1)}$	31	−0.3625	0.005117	−0.00013502	4.386	7.77	0.56

Optimal values of parameters in Equation (1), correlation coefficients and the results of Fisher test applications.

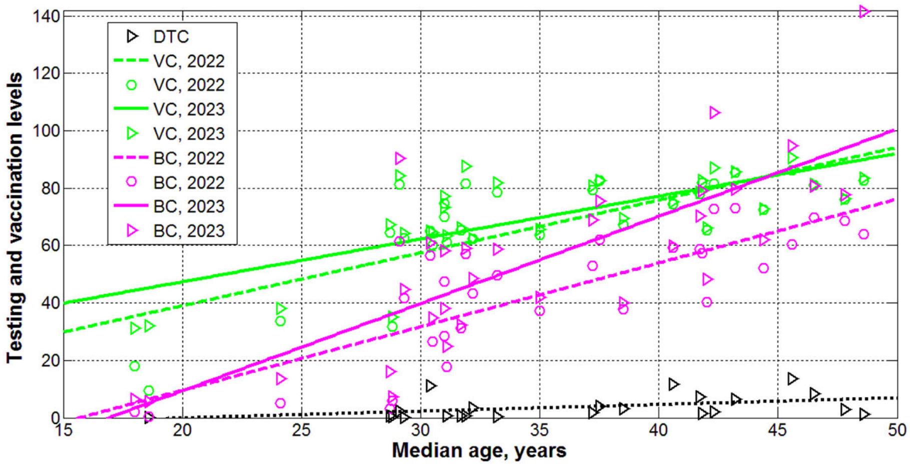

FIGURE 4
Levels of testing (black), vaccinations (green) and boosters (magenta) in 2022 ("circles") and 2023 ("triangles") vs. median age. Best fitting lines are solid for 2023 and dashed for 2022. The dotted line corresponds to the *DTC* correlation (supported at the significance level 0.05).

Table 5 and displayed in Figure 4. We can see strong correlations between $VC^{(1)}$, $VC^{(2)}$, $BC^{(1)}$, and $BC^{(2)}$ vs. median age of population A (see rows 2–5 in Table 5; green and magenta best fitting lines in Figure 4). The correlation between A and DTC is supported at the confidence level 0.05 (see the first row in Table 5 and the black best fitting line in Figure 4). The growth of the median age leads to the increase of testing level and the percentage of vaccinations and boosters. These correlations can be a result of higher incomes in aged countries and more vaccinations and boosters in older people.

Now we can explain why the numbers of cases and deaths per capita can increase with increasing the percentages of fully vaccinated people and boosters (see rows 2, 3, 6, 7, 9, 10, 13, 14 in Table 4 and green and magenta best fitting lines in Figures 1, 2)? Values $VC^{(1)}$, $VC^{(2)}$, $BC^{(1)}$, and $BC^{(2)}$ are not independent and definitely increase with the age. On the other hand, *DCC* and *DDC* values also increase with growth of A_i (see rows 1, 5, 8, 12 in Table 4 and blue best fitting lines in Figures 1, 2). To remove the influence of age in correlations between vaccinations and *DCC* and *DDC* values, let us consider the "purified" variations of $VC^{(1)}$and $BC^{(1)}$ (we limited ourselves only to 2022 with more reliable statistical data):

$$VP_i = VC_i^{(1)} - (2.3288 + 1.8376A_i)\,; \qquad i = 1, 2, .., 34$$

$$BP_i = BC_i^{(1)} - (-34.8469 + 2.2198A_i)\,; \qquad i = 1, 2, .., 34$$

To obtain the "purified" variations the percentages of vaccinations VP_i and boosters BP_i, we have excluded from variations $VC^{(1)}$and $BC^{(1)}$ the values predicted by the by the best fitted lines listed in Table 5 (rows 2 and 4).

We have used the linear regression (Equation 6) and Fisher test to find correlations between *DCC*, *DDC* and *CFR* values and explanatory variables *VP* and *BP*. The results of calculations are listed in Table 5 (lines 6–11). No correlations were revealed at the confidence level 0.01. Thus, the vaccinations and booster themselves do not increase the numbers of cases and death per capita. No correlations between *VC* and the numbers of cases and deaths per capita accumulated in 15 European countries with the highest testing level as of August 1, 2022 were revealed at the confidence level 0.05 (Nesteruk and Rodionov, 2022b). The lack of decreasing trends and fact that severe pandemic waves occurred in countries with high vaccination levels [e.g., Israel, Hong Kong and Japan (Nesteruk, 2021a, 2022)] call into question the effectiveness of vaccinations due to coronavirus mutations (see text footnotes 5–8) and large numbers of re-infections (see text footnote 9, Flacco et al., 2022; Guedes et al., 2023).

As expected, the case fatality risks reduce for higher values of *VP* and *BP* (see lines 8, 11 in Table 5), but at lower confidence level than vs. $VC^{(1)}$and $BC^{(1)}$ (see lines 16 and 17 in Table 4).

Conclusions

The averaged daily numbers of cases *DCC* and death *DDC* per million, case fatality risks *DDC/DCC* were calculated for 34 countries and regions with the use of John Hopkins University (JHU) datasets for numbers per capita accumulated in 2022 and 2023. Linear and non-linear approaches were used to find correlations with the averaged daily numbers of tests per thousand *DTC*, median age of population *A*, and percentages of vaccinations *VC* and boosters *BC*.

One-year increment in the median age yielded 39.8 increase in *DCC* values and 0.0799 DDC increase in 2022 (in 2023 these figures are 5.8 and 0.0263, respectively). With decreasing of testing level *DTC* the case fatality risk can increase drastically. *DCC* and *DDC* values increase with increasing the percentages of fully vaccinated people and boosters. Since *VC* and *BC* values definitely increase with at higher *A*, the corrected variations of *VC* and *BC* were introduced, which showed no correlations with *DCC* and *DDC* values.

The presented analysis demonstrates that age is a pivot factor in visible (registered) part of the COVID-19 pandemic dynamics. Much younger Africa has registered less numbers of cases and death per capita due to many unregistered asymptomatic patients. Of great concern is the fact that COVID-19 mortality in 2023 in the UK is still at least 4 times higher than the global value caused by seasonal flu.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

IN: Writing—original draft, Writing—review & editing, Data curation, Investigation, Methodology, Software.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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